FRANCIS X. DIEBOLD
KAMIL YILMAZ

Financial and Macroeconomic Connectedness

A Network Approach to Measurement and Monitoring

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To our families:
Susan, Hannah, Frank, and Gillian
Sibel, Lara Zeynep, and Elif Mina

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PREFACE

Issues of connectedness arise everywhere in modern life, from power grids to social networks, and nowhere are they more central than in finance and macroeconomics—two areas that are themselves intimately connected. The global crises of 1997–1998 (the "Asian Contagion") and 2007–2009 (the "Great Recession") are but two recent reminders, with countless ancestors and surely countless progeny. But financial and economic connectedness nevertheless remains poorly defined and measured and hence poorly understood.

Against this background, we propose a simple framework for defining, measuring, and monitoring connectedness. We focus on connectedness in financial and related macroeconomic environments (cross-firm, cross-asset, cross-market, cross-country, etc.). Our scope is in certain respects desirably narrow—specific tools for specific problems—but in other respects also desirably broad, as issues of connectedness arise everywhere in finance and economics.

Our work stems from our struggle to understand the Asian Contagion during a 2003–2004 Yilmaz sabbatical working with Diebold at the University of Pennsylvania, along with struggle to understand the Great Recession during a second 2010–2011 Yilmaz sabbatical with Diebold at the same institution. Fascinating questions surround those crises, and many others, past and future: How can we conceptualize and measure connectedness at different levels of granularity, from highly disaggregated (pairwise) through highly aggregated (system-wide)? Does connectedness vary through time, and if so, how and why? Is connectedness related to crises, and can connectedness measurement be used to improve risk management? Asset allocation? Asset pricing? Can it be used to improve public policy and regulatory oversight?

We opted for a book rather than a large set of separate journal articles for two reasons. First, because the underlying methodological framework is the same for each application, the book format lets us develop the theory first and then draw upon it repeatedly in subsequent chapters, without re-expositing the theory. Second, we feel strongly that our whole is greater than the sum of its parts (much as we like the parts!). That is, the natural complementarity of our analyses across assets, asset classes, firms, countries, and so on, makes a book an unusually attractive vehicle for describing our methods and thoroughly illustrating the breadth of their applications.

We hope that the book will interest a broad cross section of students, researchers, and professionals in finance and economics. Specifically, it should be of use to academics at a variety of levels, from advanced undergraduates, to masters and Ph.D. students, to cutting-edge researchers. Simultaneously, it should interest professionals in financial services, asset management, and risk management. In addition, the book should interest those in official organizations such as central banks, country fiscal and regulatory authorities, and nongovernment organizations. Indeed, although we are economists and our intended audience is largely economists (broadly defined), issues of connectedness go far beyond economics, and we hope that our ideas will resonate more widely, ranging from (a) technical areas such as applied mathematics, statistics, and engineering to (b) applied areas like political science and sociology.

The book's structure is very simple. Chapter 1 provides the foundation on which the rest of the book builds, defining and presenting methods for measuring connectedness, in population and in sample, and we relate our approach to modern network theory. The remaining chapters then apply our methods to connectedness measurement in a variety of contexts. Many of the ideas developed in earlier chapters run throughout later ones, which contain generalizations, specializations, and variations that are usefully compared and contrasted. In Chapter 2 we examine U.S. asset classes, in Chapter 3 we examine equities of individual major U.S. financial institutions, in Chapter 4 we examine global equities, in Chapter 5 we examine sovereign bond markets, in Chapter 6 we examine foreign exchange markets, in Chapter 7 we examine multiple asset classes and multiple countries, and in Chapter 8 we examine the global business cycle in real activity.

Many people and organizations have contributed to the development of this work. For helpful comments we thank conference and seminar participants, and for financial support we thank the U.S. National Science Foundation (NSF), the Sloan Foundation, and the Scientific and Technological Research Council of Turkey (TUBITAK) for Grant No. 111K500. We are especially grateful to Michael Binder, Christian Brownlees, Nuno Crato, Kathryn Dominquez, Mardi Dungey, Rene Garcia, Raquel Gaspar, Craig Hakkio, Peter Hansen, Ayhan Kose, Andrew Lo, Asgar Lunde, Vance Martin, Barbara Ostdiek, Esther Ruiz, Vanessa Smith, Erol Taymaz, and Dimitrios Tsomocos. For research assistance we thank Gorkem Bostanci, Fei Chen, Mert Demirer, Deniz Gok, Engin Iyidogan, and Metin Uyanik.

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Finally, before proceeding further, we apologize in advance for the many errors of commission and omission that surely remain, despite our efforts to eliminate them.

University of Pennsylvania Francis X. Diebold
Koç University Kamil Yilmaz

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This book draws upon certain of our earlier writings, including:

"Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets," *Economic Journal*, **119**, 158–171, 2009.

"Equity Market Spillovers in the Americas," in R. Alfaro (ed.) *Financial Stability, Monetary Policy, and Central Banking*, Bank of Chile, Santiago, 2011.

"Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers" (with discussion), *International Journal of Forecasting*, **28**, 57–66, 2012.

"On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms," *Journal of Econometrics*, **182**, 119–134, 2014.

"Measuring the Dynamics of Global Business Cycle Connectedness," in S. J. Koopman and N. Shephard (eds.), *Unobserved Components and Time Series Econometrics: Festschrift in Honor of Andrew Harvey's 65th Year*, Oxford University Press, New York, 2015, in press.

Financial and Macroeconomic Connectedness

1

MEASURING AND MONITORING FINANCIAL AND MACROECONOMIC CONNECTEDNESS

All knowledge is connected to all other knowledge. The fun is in making the connections.
[Arthur Aufderheide, Paleopathologist (a.k.a. "The Mummy Doctor") 1922–2013]

In this book we develop theoretically rigorous yet practically (i.e., empirically) relevant measures of connectedness for use primarily in financial markets. Our interest centers on financial market connectedness because of its centrality for understanding the workings of the markets, as well as for successfully navigating core financial market activities like risk management, portfolio allocation, and asset pricing. In financial markets we are often interested in connections among different assets, asset classes, portfolios, and so on. The objects connected are typically returns or return volatilities.

Associated with financial markets are (a) networks of financial institutions, such as retail banks, wholesale banks, investment banks, and insurance companies, and (b) asset management firms, such as mutual funds and hedge funds. Hence we are interested in measuring connectedness not only among aggregate markets, but also among individual institutions via, for example, individual firm equity returns.

Finally, financial assets are, of course, claims on real output streams, which are the fundamentals that determine prices. Hence our interest in financial markets also implies interest in underlying macroeconomic fundamentals. And if financial markets are in part driven by macroeconomic fundamentals (aspects of the business cycle, inflation, etc.), then the converse is also true: The macroeconomy is in part driven by financial markets, as emphasized for example by the Great Recession of 2007–2009, which was preceded by financial crisis.

1.1 MOTIVATION AND BACKGROUND

In this section we elaborate on the importance of connectedness in financial contexts, stressing the role of connectedness among various financial risks. We proceed for now at a verbal intuitive level, reserving rigorous definition of connectedness for later sections. We highlight the many areas in which issues of connectedness appear (risk management, portfolio allocation, business-cycle analysis, etc.), and we also introduce the idea of connectedness measurement for real-time crisis monitoring, an idea that recurs throughout the book.

1.1.1 Market Risk

Risk measurement is a basic ingredient to successful risk management. Huge attention and resources are therefore devoted to measuring various financial risks. One of the most fundamental is market risk, the risk of changes in portfolio value due to changes in the value of its underlying components. Connectedness is presumably part of any comprehensive market risk assessment, because it separates the risk of a portfolio from the risk of its underlying components. That is, the risk of a portfolio is not simply a weighted sum of the risks of its components. Overall portfolio risk depends on how the pieces interact—whether and how they are connected. The likelihood of extreme market movements, typically associated with all or most assets moving in the same direction, depends on connectedness.

1.1.2 Portfolio Concentration Risk

Thus far we have emphasized risk measurement considerations, emphasizing that connectedness is what separates portfolio risk from the sum of component risks. But portfolio allocation is about minimizing portfolio risk, so optimal portfolio allocation must require awareness and measurement of connectedness. That is, connectedness must govern "portfolio concentration risk," which determines the scope of effective diversification opportunities.

Exogenous Aspects

Note that time-varying connectedness implies time-varying diversification opportunities. Connectedness may be relatively low much of the time, for example, implying good diversification opportunities. In crises, however, connectedness may increase dramatically, implying a loss of diversification just when it is needed most. Skillful timing of portfolio shares to exploit time-varying connectedness can potentially be exploited to generate extra risk-adjusted excess returns, as in Fleming et al. (2001), Fleming et al. (2003), Kyj et al. (2009), and Kirby and Ostdiek (2012).

Endogenous Aspects

Our discussion thus far has the flavor of time-varying portfolio concentration risk arising due to time-varying connectedness, due in turn to factors beyond the control of portfolio managers. Often that is the case. It is interesting to note, however, that time-varying connectedness can also be caused by managers themselves. Disparate portfolio management styles, for example, may converge over time, as style information is disseminated and recipes for the "secret sauce" are effectively shared and eventually combined. Khandani and Lo (2007), for example, examine return correlations across 13 hedge fund styles in 1994–2000 and in 2001–2007.[1] They find a substantial increase in connectedness over time, presumably due to a gradual blending of styles.

Factor Structure

Special structure is often operative in portfolio management and asset pricing contexts, with implications for connectedness. In particular, factor structure is often relevant. To take a simple example, consider a one-factor model,

$$y_t = \lambda f_t + \varepsilon_t,$$

where $f_t \sim WN(0, \sigma^2)$ and $\varepsilon_t \sim WN(0, \Sigma)$, with f_t and ε_t orthogonal. In the simplest setup, Σ is diagonal, in which case, other things being equal, connectedness would seem surely linked to the factor loadings λ, and perhaps also to the ratios of the factor variance σ^2 to the variances in Σ (the "signal-to-noise ratios"). Time-varying connectedness would then arise through time-varying loadings and/or signal-to-noise ratios. In richer environments, but still with factor structure, Σ might be nondiagonal, or sometimes diagonal and sometimes not (e.g., in normal versus crisis times, as in Dungey et al. (2011)), producing additional time variation in connectedness.

[1] The styles are convertible arbitrage CA, dedicated short bias DSB, emerging markets EM, equity market neutral EMN, event-driven ED, fixed income arbitrage FIA, global macro GM, long–short equity hedge LSEH, managed futures MF, event-driven multi-strategy EDMS, distressed index DI, risk arbitrage RA, and multi-strategy MS.

Ignoring Connectedness

Far more often than not, one ignores connectedness to one's detriment. Interestingly, however, some work exploits connectedness by intentionally ignoring it. A recent example is DeMiguel et al. (2009), who study the comparative performance of simple equally weighted portfolios. In traditional portfolio theory, equal weights are "optimal" only if underlying returns have equal variance and zero covariance. They find good performance of the simple strategies that ignore connectedness, evidently because in their environment connectedness is estimated so imprecisely that attempts to include it do more harm than good. The relevant point is that even a decision to *ignore* connectedness nevertheless entails awareness of it, and hopefully an understanding of its nature and sources.

1.1.3 Credit Risk

The risk of a defaultable bond, and hence its price, depends on its probability of default. Bond default and related issues are so important, and so special and nuanced, that they form a separate field of credit risk.

When one considers bond *portfolios*, default *connectedness* emerges as central to portfolio risk assessment and pricing. That is, the risk associated with holding a portfolio of bonds whose defaults are independent, for example, is vastly different from the risk associated with holding a portfolio with highly connected defaults. Hence a key issue is whether the probability of a firm's defaulting depends on whether other firms are defaulting and, if so, how strongly. This is clearly a connectedness question. The same issue is relevant for sovereign credit risk, as manifest for example in the wave of 1980s Latin American sovereign defaults.

1.1.4 Counterparty and "Gridlock" Risk

Concepts like counterparty credit risk, which links balance sheets ("balance sheet risk"?), are directly linked to aspects of connectedness. Lowenstein (2010, pp. 101–102) puts it well:

> Since events affecting borrowers are certain to affect lenders, and since institutions simultaneously borrow and lend with multiple parties, credit results in a complex network in which every financial participant is dependent on the rest. Given that even a single bond issuer may have thousands of lenders, the potential for a chain-reaction panic is clear. Lenders not only fear for the borrowers, but for the borrower's borrowers—and for how a panic would affect them all.

Hence, and perhaps surprisingly at first, counterparty risk is fundamentally multilateral rather than bilateral—really a sort of "congestion risk," or "gridlock risk" in the colorful parlance of Brunnermeier (2009).

Connectedness may also to be related to the concept of liquidity risk, but traditional theory links liquidity to variation (which widens spreads) rather than covariation or more general connectedness. Of course, if variation (volatility) and connectedness move together (e.g., increasing during crises), then connectedness and liquidity may be related.

1.1.5 Systemic Risk

In a well-known survey, DeBandt and Hartmann (2000) provide an oft-cited definition of systemic risk:

> A systemic crisis can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system. . . . Systemic risk goes beyond the traditional view of single banks' vulnerability to depositor runs. At the heart of the concept is the notion of . . . particularly strong propagation of failures from one institution, market or system to another.

This definition clearly involves aspects of connectedness.

Systemic risk measurement is central for best-practice private-sector competitive strategy. Total systemic risk measurement may be a useful ingredient to worst-case scenario planning (stress testing), and single-firm systemic risk measurement is useful for helping guide strategic planning and relationship building. The basic questions are "If everyone else tanks, what happens to me?" and "If firm *x* tanks, what happens to me?"

Of greater attention lately, measurement of systemic risk is also a prime concern of financial institution regulators. Regulators may be interested in total systemic risk ("How connected are all firms?") or single-firm systemic risk ("How connected are all other firms, taken as a set, to firm *x*?"). For example, policy toward systemic risk (e.g., taxing financial institutions according to their connectedness, as in Acharya et al. (2009) and Acharya et al. (2010)) first requires a connectedness measurement. Hence a connectedness measurement is a key tool for macro-prudential policymaking. In any event, the Dodd–Frank Act and its Financial Stability Oversight Committee *require* quantitative measures of systemic risk.

Recent work by Brunnermeier et al. (2012) on systemic risk measurement also features connectedness prominently. Their two-step procedure first incorporates partial equilibrium effects (as in micro-prudential regulation) but then incorporates macro-prudential aspects of connectedness via general equilibrium effects. More precisely, risk factors and factor sensitivities are calculated at the firm level, directly by firms, who are in the best position to undertake the necessary modeling. The connectedness is calculated at the system-wide level by the regulator, who is similarly in the best position to undertake the necessary modeling.

1.1.6 Business Cycle Risk

The business cycle is the key fundamental that drives asset prices, as emphasized by Fama and French (1989), Fama (1990), and Campbell and Diebold (2009), among many others. That is, business cycle risk is a key priced systematic risk. Business cycles are a multivariate phenomenon closely linked to aspects of connectedness, as emphasized in domestic contexts by Lucas (1977) and in global contexts by Gregory et al. (1997), Dees et al. (2007), and Aruoba et al. (2011). Indeed assessment of business cycle risk requires assessment of connectedness, as the systematic nature of business cycle risk (whether domestic or global) is crucially linked to connectedness: Disconnected risks can be diversified and hence cannot be systematic.

Quite apart from its role in driving risk premia on financial assets, real activity connectedness is of independent interest. Here we offer four brief examples. First, connectedness of real activity across sectors within a country, or across countries, is intimately related to ongoing discussion of issues such as globalization, synchronization, decoupling, and recoupling.[2] Second, certain aspects of financial systemic risk thinking also involve real activity, as many view the systemic risk of a financial firm as linked to the likelihood that its failure would effect the real economy. Third, business cycle expectations are a key driver of equity market risk premia, suggesting the importance of monitoring connectedness between real activity and stock returns. Finally, the famously shifting Phillips curve involves the (shifting) connectedness between real activity and inflation.

1.1.7 Financial and Macroeconomic Crisis Monitoring

If connectedness measurement is useful in the variety of situations as sketched thus far, it is also potentially useful in a less obvious but very important mode, crisis monitoring, because (as we shall see) connectedness tends to increase sharply during crises. Hence a sub-theme of real-time dynamic crisis monitoring runs throughout this book.

[2] Indeed the idea of connectedness of real activities via input–output relations in general equilibrium goes back centuries, to Quesnay's Tableau Economique.

The details depend on context, but here we supply a bit of background on some of the crises that form the backdrop for our subsequent empirical analyses.

One interesting regularity is that emerging-market shocks tend to be large but typically localized, whereas developing-market shocks tend to be smaller but often have broader systemic impact. Consider, for example, three key recent large shocks to emerging markets. First, following seven years of growth with high current account deficits financed by external capital inflows, Mexico plunged into financial crisis in late 1994, and Mexican GDP fell by 6.2% in 1995. The ripple effects, however, were limited to Latin America. Second, East Asia experienced a severe financial crisis in 1997, effectively caused by a bursting real estate bubble financed by external capital inflows. The crisis had major impact in Asia, but effects outside Asia were muted. Finally, the Russian crisis of 1998, caused by Russia's inability to service its debt, inflicted serious damage on the region and some European countries, but the ripple effects were again quite small.

Now consider, in contrast, three key recent smaller shocks to the United States: the bursting of the dot-com bubble, the LTCM episode, and the WorldCom scandal. The bursting of the dot-com bubble during 2000–2001 was an important event, starting with a decline in the Nasdaq and followed by orderly downward moves in other major U.S. indexes, but it is hard to label it a crisis. Similarly, the LTCM episode was hardly a full-blown crisis; rather, it was a market hiccup due to the troubles of a single hedge fund. The WorldCom scandal was also a comparatively minor event; it had significant impact on U.S. financial stocks, but little impact on other U.S. equities. The key observation is that in each case, the small U.S. shocks nevertheless had substantial impact globally, with U.S. market declines and increased volatility leading to substantial global market losses.

1.1.8 A Final Remark

We have chosen to introduce connectedness in this section via considerations of *risk*, along with the contribution of connectedness to risk in multivariate environments. Risk is sometimes viewed as undesirable, and one might infer that connectedness is necessarily undesirable. We hasten to add that such inferences are incorrect for at least two reasons.

First, risk is of course *not* undesirable in the sense that it should necessarily be avoided. Literally millions of people and firms routinely and voluntarily choose to bear financial risks of various types, because risk is the key to return. As they say, "no risk, no return." The key is to assess risks accurately, including risk components due to connectedness, so that the required return can be assessed with similar accuracy.

Second, connectedness in financial contexts extends beyond risk considerations, at least as traditionally conceptualized, and certain types of connectedness may be directly desirable. For example, connectedness can arise from and vary with risk sharing via insurance, links between sources and uses of funds as savings are channeled into investments, patterns of comparative advantage that generate international trade, regional and global capital market integration, and enhanced coordination of global financial regulation and accounting standards.

Ultimately it is not useful to attempt to label different types of connectedness as "good" or "bad." Rather, connectedness is simply *important*, and the ability to measure it accurately is therefore useful.

1.2 THE CONNECTEDNESS TABLE

Our approach to connectedness is based on assessing shares of forecast error variation in various locations due to shocks arising *elsewhere*. This is intimately related to the familiar econometric notion of a variance decomposition: The H-step forecast error variance share d_{ij} is just the fraction of i's H-step forecast error variance due to shocks in variable j.[3] The full set of variance decompositions produces the core of what we call the *connectedness table*. All of our connectedness measures—from simple pairwise to system-wide—flow from the connectedness table. In Section 1.2.1 we introduce the connectedness table for a given variance decomposition, and in Section 1.2.2 we place our approach in some perspective. In Section 1.2.3 we discuss various ways of obtaining (identifying) variance decompositions.

1.2.1 Decomposing Variation

The simple Table 1.1, which we call a *connectedness table*, proves central for understanding the various connectedness measures and their relationships. Its main upper-left $N \times N$ block contains the variance decompositions. For future reference we call that upper-left block a "variance decomposition matrix," and we denote it by $D = [d_{ij}]$. The connectedness table simply augments D with a rightmost column containing row sums, a bottom row containing column sums, and a bottom-right element containing the grand average, in all cases for $i \neq j$.

To understand and interpret the information conveyed by the connectedness table, it is helpful to cut through the notational clutter via a simple example, as in the example connectedness Table 1.2 with $N = 4$. The 12 off-diagonal entries in the upper-left

[3] Note that, formally, we should use a notation that indicates the dependence of d_{ij} on H. We shall emphasize that dependence later. For now we rely on the reader to remember but suppress it in the notation.

Table 1.1 Connectedness Table

	x_1	x_2	$\cdots$	x_N	*From Others*
x_1	d_{11}	d_{12}	$\cdots$	d_{1N}	$\Sigma_{j=1}^{N} d_{1j}, j \neq 1$
x_2	d_{21}	d_{22}	$\cdots$	d_{2N}	$\Sigma_{j=1}^{N} d_{2j}, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}	d_{N2}	$\cdots$	d_{NN}	$\Sigma_{j=1}^{N} d_{Nj}, j \neq N$
To Others	$\Sigma_{i=1}^{N} d_{i1}$ $i \neq 1$	$\Sigma_{i=1}^{N} d_{i2}$ $i \neq 2$	$\cdots$	$\Sigma_{i=1}^{N} d_{iN}$ $i \neq N$	$\frac{1}{N} \Sigma_{i,j=1}^{N} d_{ij}$ $i \neq j$

Table 1.2 Example Connectedness Table

	x_1	x_2	x_3	x_4	*From Others*
x_1	96	1	2	1	4
x_2	28	67	1	3	32
x_3	14	14	70	1	29
x_4	18	11	5	65	34
To Others	60	26	8	5	24.8

4×4 D matrix are the 12 pieces of the four forecast-error variance decompositions, d_{ij}. From a connectedness perspective, they measure *pairwise directional connectedness.* The 3,2 entry of 14, for example, means that shocks to x_2 are responsible for 14 percent of the H-step-ahead forecast error variance in x_3. We write $C_{3\leftarrow 2} = 14$. In general the pairwise directional connectedness from j to i is

$$C_{i\leftarrow j} = d_{ij}.$$

Note that in general $C_{i\leftarrow j} \neq C_{j\leftarrow i}$. Hence there are $N^2 - N$ separate pairwise directional connectedness measures. They are analogous to bilateral imports and exports for each of a set of N countries.

Sometimes we are interested in *net* pairwise directional connectedness, in a fashion analogous to a bilateral trade balance. For example, for x_2 and x_3 we have $C_{23} = C_{3\leftarrow 2} - C_{2\leftarrow 3} = 14 - 1 = 13$. In general we have

$$C_{ij} = C_{j\leftarrow i} - C_{i\leftarrow j}.$$

There are $\dfrac{N^2 - N}{2}$ net pairwise directional connectedness measures.

The 8 off-diagonal row and column sums, labeled "from" and "to" in the connectedness table, are the 8 *total directional connectedness* measures. The value of 32 in the second entry of the rightmost column, for example, means that x_2 receives 32 percent of its variation from others (x_1, x_3, and x_4). We write $C_{2\leftarrow\bullet} = 28 + 1 + 3 = 32$. In general the total directional connectedness from others to i is

$$C_{i\leftarrow\bullet} = \sum_{\substack{j=1\\ j\neq i}}^{N} d_{ij},$$

and the total directional connectedness from j to others is

$$C_{\bullet\leftarrow j} = \sum_{\substack{i=1\\ i\neq j}}^{N} d_{ij}.$$

Hence there are $2N$ total directional connectedness measures, N "to others" and N "from others," analogous to "total exports" and "total imports" for each of a set of N countries.

Just as with pairwise directional connectedness, sometimes we are interested in net total directional effects. For x_2, for example, we have $C_2 = C_{\bullet\leftarrow 2} - C_{2\leftarrow\bullet} = 26 - 32 = -6$. In general, net total directional connectedness is

$$C_i = C_{\bullet\leftarrow i} - C_{i\leftarrow\bullet}.$$

There are N net total directional connectedness measures, analogous to the total trade balances of each of a set of N countries.

Finally, the grand total of the off-diagonal entries in D (equivalently, the sum of the "from" column or "to" row) measures *total (system-wide) connectedness*. We typically express this total cross-variable variance contribution, given in the lower right cell of the connectedness table, as a percent of total variation. Hence total connectedness in our example is $C = \frac{99}{400} \times 100 = \frac{99}{4} = 24.8$.[4] In general we have

$$C = \frac{1}{N}\sum_{\substack{i,j=1\\ i\neq j}}^{N} d_{ij}.$$

[4] Note that total variation is just 100 times N, the number of variables in the system, because each of the N rows sums to 100. Conversion to percent eliminates the 100, so that ultimately total connectedness is simply average total directional connectedness (whether "from" or "to").

There is just a single total connectedness measure, as total connectedness distills a system into a single number analogous to total world exports or total world imports (the two are of course identical).

The connectedness table makes clear how one can begin with the most disaggregated (e.g., microeconomic, firm-level pairwise directional) connectedness measures and aggregate them in various ways to obtain macroeconomic economy-wide total directional and total connectedness. Different agents may be disproportionately interested in one or another of the measures. For example, firm i may be maximally interested in total directional connectedness from others to i, $C_{i\leftarrow\bullet}$, whereas regulators might be more concerned with total directional connectedness from i to others, $C_{\bullet\leftarrow i}$, or with total connectedness C.

1.2.2 Perspectives on Our Approach

Our approach is nonstructural and empirical/statistical. There are associated costs and benefits, which we now discuss in greater detail.

Nonstructural

Our approach is intentionally nonstructural. We seek connectedness measures that are informed by financial and economic theory and that help to inform future theory, but that are not wed to a particular theory. In particular, we remain agnostic on *how* connectedness arises; rather, we take it as given and seek to measure it correctly for a wide range of possible underlying causal structures, which might reflect runs, network linkages, herd behavior, fire sales, policy action and feedback, and much else. Obviously there are trade-offs, but we prefer an approach that achieves much under minimal assumptions, in contrast to an approach that in principle could achieve even more, but only under heroic assumptions, and that may not be robust to violations of those assumptions. Whatever the underlying causes, we simply seek to measure the resulting connectedness.

A useful analogy may perhaps be made to the volatility literature, where the concepts of ex ante (expected) and ex post (integrated) volatility are commonplace.[5] Estimation of expected volatility (e.g., conditional variance) requires a model, and the accuracy of estimated expected volatility may depend crucially on the model. In contrast, consistent estimation of integrated volatility may proceed in model-free fashion using realized volatility.

[5] For an overview see Andersen et al. (2010).

Empirical/Statistical

Our approach is unabashedly empirical/statistical, in the tradition of Kelvin (1891), who makes the general case:

> When you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meager and unsatisfactory kind: it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of science.

Moreover, there is a particular case for connectedness measurement at present, because recent regulatory initiatives following the financial crisis and recession of 2007–2009, such as the U.S. Dodd–Frank Act, require quantitative measurement.

Numerous subtleties arise, however, in the statistical measurement of connectedness in financial and macroeconomic environments. Schweitzer et al. (2009, p. 423) put it well:

> In the complex-network context, "links" are not binary (existing or not existing), but are weighted according to the economic interaction under consideration. . . . Furthermore, links represent traded volumes, invested capital, and so on, and their weight can change over time.

Our methods confront the issues raised by Schweitzer et al. We seek connectedness measures at all levels—from system-wide to pairwise—that are rigorous in theory and readily implemented in practice, that capture the different strengths of different connections, and that capture time variation in connectedness.

Having identified "realized connectedness," we can of course attempt to correlate it with other variables, whether in purely exploratory mode or as suggested by economic theory. For example, a variety of considerations ranging from economic theory to simple introspection suggest that connectedness may increase during crises, as everyone runs for the exits simultaneously. Thus, for example, one might examine the correlation between U.S. equity connectedness and the VIX ("the investor fear gauge"). Related, interesting recent work by Bloom et al. (2012) suggests strong recession effects in both stock return volatility and real output volatility, so one might check whether stock connectedness and output component connectedness increase in recessions.

Relationship to Stress Testing

Our methods are related to, but distinct from, recent developments in the risk management stress-testing literature. The idea of stress testing is to see how a shock scenario in one area impacts other areas.

Important recent literature approaches stress testing from an explicit network perspective. Rebonato (2010), for example, builds on earlier work by Berkowitz (1999), as well as on the literature on graphical models, Bayesian networks, and causal statistical modeling, as in Pearl (2000).[6]

As we will show in detail, our methods are also very much driven by a network perspective.

1.2.3 Identifying Shocks

As already emphasized, our approach is based on variance decompositions. An H-step forecast error variance decomposition d_{ij} answers an interesting and important question: What fraction of H-step forecast error variance of variable i is due to shocks in *another* variable j? Here we review strategies for obtaining variance decompositions.

Orthogonal Shocks

Consider an N-dimensional data-generating process (DGP) with orthogonal shocks:

$$x_t = A(L)u_t,$$
$$A(L) = A_0 + A_1L + A_2L^2 + \cdots,$$
$$E(u_tu_t') = I.$$

Note that A_0 need not be diagonal.

All aspects of connectedness are contained in this very general representation. In particular, contemporaneous aspects of connectedness are summarized in A_0, and dynamic aspects are summarized in $\{A_1, A_2, \ldots\}$. Nevertheless, attempting to understand connectedness by staring at (literally) hundreds of elements of $\{A_0, A_1, A_2, \ldots\}$ is typically fruitless. One needs a transformation of $\{A_0, A_1, A_2, \ldots\}$ that better reveals connectedness. Variance decompositions achieve this.

In the orthogonal system above, the variance decompositions are easily calculated, because orthogonality ensures that the variance of a weighted sum is simply an appropriately weighted sum of variances. In the more realistic case of correlated shocks, to

[6] For recent developments see Chalak and White (2011).

which we now turn, the calculations are more involved but identical in spirit. We need to isolate the independent shocks that underlie the observed system.

Correlated Shocks

Consider a DGP with moving-average representation,

$$x_t = \Theta(L)\varepsilon_t,$$
$$E(\varepsilon_t\varepsilon_t') = \Sigma,$$

with nonorthogonal shocks.

One way or another, we must transform the shocks to orthogonality to calculate variance decompositions. The orthogonalization can be handled in several ways, to which we now turn.

Cholesky Factorization

This time-honored method traces at least to Sims (1980). Consider a DGP with correlated shocks,

$$x_t = \Theta(L)\varepsilon_t,$$
$$E(\varepsilon_t\varepsilon_t') = \Sigma.$$

The correlated-shocks model is mathematically identical to the orthogonal-shocks model,

$$x_t = A(L)u_t,$$
$$E(u_t u_t') = I,$$
$$A(L) = \Theta(L)Q,$$
$$u_t = Q^{-1}\varepsilon_t,$$

where the lower triangular matrix Q is the Cholesky factor of Σ; that is, $QQ' = \Sigma$. Hence a simple Cholesky-factor transformation orthogonalizes the system.

Generalized Variance Decompositions

The generalized variance decomposition (GVD) framework of Koop et al. (1996) and Pesaran and Shin (1998) produces variance decompositions invariant to ordering. The GVD approach does not require orthogonalized shocks; rather, it allows and accounts for correlated shocks using the historically observed error distribution, under a normality assumption.

The GVD matrix $\Delta = [\delta_{ij}]$ has entries

$$\delta_{ij} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)},$$

where e_j is a selection vector with j^{th} element unity and zeros elsewhere, A_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the nonorthogonalized VAR, Σ is the covariance matrix of the shock vector in the nonorthogonalized VAR, and σ_{jj} is the j^{th} diagonal element of Σ.[7]

Because shocks are not necessarily orthogonal in the GVD environment, sums of forecast error variance contributions (that is, row sums in GVD matrices) are not necessarily unity $\left(\sum_{j=1}^{N} \delta_{ij} \neq 1\right)$. Hence we base our generalized connectedness indexes not on Δ, but rather on $\tilde{\Delta} = [\tilde{\delta}_{ij}]$, where

$$\tilde{\delta}_{ij} = \frac{\delta_{ij}}{\sum_{j=1}^{N} \delta_{ij}}.$$

Note that, by construction, $\sum_{j=1}^{N} \tilde{\delta}_{ij} = 1$ and $\sum_{i,j=1}^{N} \tilde{\delta}_{ij} = N$. Armed with $\tilde{\Delta}$, we can immediately calculate generalized connectedness measures $\tilde{C}$, $\tilde{C}_{\bullet\leftarrow j}$, $\tilde{C}_{i\leftarrow\bullet}$, $\tilde{C}_i$, $\tilde{C}_{i\leftarrow j}$, $\tilde{C}_{j\leftarrow i}$, and $\tilde{C}_{ij}$.

In essence the GVD does not impose orthogonality of shocks. Therefore, in the GVD framework all variables in a system are subject to shocks simultaneously. This, in return, amounts to obtaining impulse responses and variance decompositions for each variable, treating each variable as the leading variable in the VAR. Indeed, in the case of networks where all actors/nodes/vertices are equal ex ante, allowing for a shock to hit all nodes simultaneously and cascade through the network is a logical exercise to consider, in contrast to assuming a priori that some nodes are exogenous relative to others.

"Structural" VARs

One may also use restrictions from economic theory, if available, to identify variance decompositions. Consider the structural system:

$$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + Q u_t, \quad u_t \sim (0, I).$$

[7] Note the typo in the original paper of Pesaran and Shin (1998, p. 20). In the equation where they introduced the generalized variance decompositions, they wrote σ_{ii}^{1} but should have written σ_{jj}^{-1}.

The reduced form is

$$\begin{aligned} y_t &= A_0^{-1}A_1y_{t-1} + \cdots + A_0^{-1}A_py_{t-p} + A_0^{-1}Qu_t \\ &= \Phi_1y_{t-1} + \cdots + \Phi_py_{t-p} + \varepsilon_t. \end{aligned}$$

Note that $\varepsilon_t = A_0^{-1}Qu_t$, so $u_t = Q^{-1}A_0\varepsilon_t$. Identification requires N^2 restrictions on $A_0, \ldots, A_p, Q$.

Choosing an Identification Method

The different identification strategies have different costs and benefits. The traditional Cholesky factorization is statistically—as opposed to economically—motivated and may be sensitive to ordering, as has been well-appreciated at least since Sims (1980). In the empirical work in subsequent chapters, we will often check and report results for all of the $N!$ possible orderings or, if N is too large, for a large number of randomly selected orderings.

The GVD approach is also statistically motivated, but the results are independent of ordering. They are, however, dependent on additional assumptions. In particular, GVDs require normality, and hence may be more useful for assessing connectedness of (log) volatilities, which are well-approximated as Gaussian, than for returns, which are not.

We often find that total connectedness is robust to ordering; that is, the range of total connectedness estimates across orderings is often quite small. Directional connectedness, however, may be more sensitive to ordering, and hence GVDs may be more useful there.

Finally, structural identification is economically—as opposed to statistically—motivated, but it requires the maintained assumption of validity of a particular economic model.

1.2.4 Toward Dynamics

Clearly, C and its directional relatives depend on the set of variables x whose connectedness is to be examined, the predictive horizon H for variance decompositions, and the dynamics $A(L)$, so we write $C(x, H, A(L))$.[8] In the Section 1.3 we will elaborate on aspects of connectedness measurement associated with x, H, and $A(L)$, but one aspect is potentially so important that we foreshadow it now: the dynamics associated with time-varying $A(L)$.

[8] The same holds, of course, for the various directional connectedness measures, so we use $C(x, H, A(L))$ as a stand-in for all our connectedness measures.

For a variety of reasons, $A(L)$ might be time varying. It could evolve slowly with evolving tastes, technologies, and institutions. It could vary with the business cycle. It could shift abruptly with the financial market environment (e.g., crisis, non-crisis).

Variation in $A(L)$ is potentially interesting and important, because it produces time-varying connectedness: If $A(L)$ varies, then so too does $C(x, H, A(L))$. Whether and how much $A(L)$ varies is ultimately an empirical matter and will surely differ across applications, but in any event it would be foolish simply to assume constancy of $A(L)$ throughout.

Allowing for variation in $A(L)$ allows us to move from the static, unconditional, perspective implicitly adopted thus far, to a dynamic, conditional perspective, to which we now turn. We will maintain that dynamic perspective for the rest of this book.

1.3 ESTIMATING DYNAMIC CONNECTEDNESS

Thus far we have discussed connectedness exclusively in population. Now we consider the *estimation* of connectedness.[9]

Clearly, C depends on x, H, and $A(L)$, so we have written $C(x, H, A(L))$. In reality, A is unknown and must be approximated (e.g., using a finite-ordered vector autoregression). Recognizing the centrality of the approximating model adopted, we write $C(x, H, A(L), M(\theta))$, where θ is a finite-dimensional parameter. In addition, we want to allow for time-varying connectedness, effectively allowing the connection table and all of its elements to vary over time, so we write $C_t(x, H, A_t(L), M(\theta_t))$.

Finally, everything we have written thus far is in *population*, whereas in reality we must use an approximating model estimated using data $1:T$, so we write $\widehat{C}_t(x, H, A_t(L), \widehat{M}_{1:T}(\hat{\theta}_t))$. To economize on notation, we henceforth drop $A(L)$, because it is determined by nature rather than a choice made by the econometrician, relying on the reader to remember its relevance and writing $\widehat{C}_t(x, H, \widehat{M}_{1:T}(\hat{\theta}_t))$.

In what follows we successively discuss aspects of selection of x, H, and $\widehat{M}_{1:T}(\hat{\theta}_t)$.

1.3.1 x

Choice of x, the object of interest to be studied, has important implications for the appropriate approximating model; for example, x may (or may not) be strongly serially correlated, conditionally heteroskedastic, or highly disaggregated.

[9] We provide annotated code implementing our methods (in R, Eviews, Ox, and Matlab) at http://www.ssc.upenn.edu/~fdiebold/ and http://home.ku.edu.tr/~kyilmaz/

Asset Returns

In financial markets, x often contains returns. Return connectedness is of direct interest. If returns track changes in investor expectations, then return connectedness tracks expectational links.

Returns tend to display little serial correlation but strong conditional heteroskedasticity, particularly when observed at relatively high frequency. They also tend to be distributed symmetrically but with fatter tails than the Gaussian. Large sets of disaggregated returns typically display factor structure.

Asset Return Volatilities

Almost equally commonly in financial markets, x contains not returns, but return *volatilities*. As with returns, volatility connectedness is of direct interest. If volatility tracks investor fear (e.g., the VIX is often touted as an "investor fear gauge"), then volatility connectedness is fear connectedness. How connected is fear? How does it spread and cluster? Volatility connectedness is also of special interest from the perspective of real-time monitoring, as volatilities tend to lurch and move together only in crises, whereas returns often move closely together in both crises *and* upswings.

Unlike returns, volatilities are latent and must be estimated. Many approaches to volatility estimation have received attention, including observation-driven GARCH-type models, parameter-driven stochastic volatility models, realized volatility, and implied volatility.[10] Volatilities tend to be strongly serially correlated (much more so than returns), particularly when observed at relatively high frequency. They also tend to be distributed asymmetrically, with a right skew, and approximate normality is often obtained by taking natural logarithms. Large sets of disaggregated return volatilities typically display factor structure.

One could go even farther and examine connectedness in various measures of time-varying higher-ordered return moments such as skewness or kurtosis. One could, for example, examine realized measures or model-based estimates. We shall not pursue that there, but recent work such as Hitaj et al. (2012) pushes in that direction.

Real Fundamentals

Alternatively, x might be a set of underlying real fundamental variables. In disaggregated environments, typical candidates would include earnings, dividends, or sales. In aggregate environments we might examine sectoral real activity within a country,

[10] For detailed discussion see Andersen et al. (2006a, 2006b, 2010).

or real activity across countries, as in Aruoba et al. (2011). Connectedness may vary, for example, with the business cycle, whether in single-country or multi-country environments.

The Reference Universe

Connectedness measurements are defined only with respect to a reference universe (set of x's). In general they will not—and should not—be robust to choice of reference universe. Hence, given a decision as to the type of x to be examined, a second important issue is precisely which (and hence how many) x's to use. For example, in cross-country analyses we may want to use sufficiently many countries to ensure that we have good global coverage. Whether this requires a small or large number of x's depends on the distribution of activity across countries. As another example, note that a reference universe of firms will change with their "births" and "deaths." Births happen, for example, when a firm goes public, and deaths happen when firms go bankrupt.

Additional Discussion

It may also be of interest to study connectedness of return factors rather than returns themselves. Equity returns, for example, are arguably driven by market, size, value, momentum, and perhaps even liquidity factors as in Pastor and Stambaugh (2003), and bond yield factors include inflation and real activity. Such risk factors may be connected in interesting ways.

Alternatively, risk factors are sometimes constructed to be orthogonal, as with principle components. But strict orthogonality may not hold, and even if true on average there may be conditional deviations from orthogonality at certain times, such as financial market crises, or recessions.

1.3.2 *H*

Certain considerations in certain contexts may help guide selection of connectedness *horizon*, H. For example, in risk management contexts, one might focus on H values consistent with risk measurement and management considerations. $H = 10$, for example, would cohere with the 10-day value at risk (VaR) required under the Basel accord. Similarly, in portfolio management contexts one might link H to the rebalancing period.

The connectedness horizon is important particularly because it is related to issues of dynamic connectedness (in the fashion of contagion) as opposed to purely contemporaneous connectedness. To take a simple pairwise example, shocks to j may impact the forecast error variance of i only with a lag, so that $C_{i \leftarrow j}$ may be tiny for small H but nevertheless large for larger H.[11] Intuitively, as the horizon lengthens, there may be more chance for things to become connected.

All told, we suggest examining a menu of H values, perhaps anchoring via risk management or asset allocation considerations, as mentioned above. In a sense, this provides a robustness check, but as we argued above, there is no reason why connectedness should be "robust" to H. Hence we view examination of a menu of H values simply as an interesting part of a phenomenological investigation. Any patterns found may be interesting and informative.

In a sense, varying H lets us break down connectedness into "long-run," "short-run," and so on. More precisely, as H lengthens we obtain a corresponding sequence of conditional prediction error variance decompositions for which the conditioning information is becoming progressively less valuable. In the limit as $H \rightarrow \infty$, we obtain an *un*conditional variance decomposition.

1.3.3 $\widehat{M}_{1:T}(\hat{\theta}_t)$

The obvious workhorse approximating model is a vector autoregression, VAR(p).[12] For returns, conditional mean dynamics in $M(\theta)$ will be relatively less important, as returns may be rather close to a vector martingale. However, conditional variance dynamics will be almost surely operative. It is not clear, however, whether conditional variance dynamics need to be explicitly modeled, as their neglect will affect the efficiency but not the consistency of the estimated VAR approximation.

For return volatilities or real activity measures, conditional mean dynamics in $M(\theta)$ will be relatively more important and will surely need to be modeled.[13] A logarithmic VAR is often appropriate for volatilities.

In addition, imposition of factor structure may be useful. Factor structure is prevalent in systems of asset returns, asset return volatilities, and macroeconomic fundamentals.[14] Dynamic factor models (DFMs) also map nicely into thinking about connectedness, which may be linked to sizes, signs, and time variation in factor loadings, as we shall discuss in some detail in Section 1.4.

[11] Such dynamic phenomena, along with the rich patterns that are possible, are closely related to aspects of multi-step Granger causality, as treated for example in Dufour and Renault (1998), Dufour and Taamouti (2010), and the references therein.

[12] Indeed we will make heavy use of vector-autoregressive approximating models in this book. For background see any good time-series econometrics text, such as Hamilton (1994).

[13] On volatility dynamics see, for example, Andersen et al. (2003), and on real activity dynamics see Aruoba and Diebold (2010).

[14] See Ross (1976), Diebold and Nerlove (1989), Aruoba and Diebold (2010), and the many references therein.

Finally, we emphasize that much more sophisticated approximating models, including deeply structural models, can be used to assess connectedness if desired. One approach is dynamic stochastic general equilibrium modeling, as implemented for example by DiNicolo and Lucchetta (2010). Another is Bayesian network modeling, as in Rebonato (2010). Whatever the model, as long as it can be used to identify an underlying set of *iid* shocks, it can be used to assess connectedness.

Time-Varying Connectedness

Connectedness is just a transformation of system coefficients. Hence if the coefficients are time-varying, so too will be connectedness. Tracking ("nowcasting") real-time connectedness movement is of central interest.

Explicitly Time-Varying Parameter Estimation

Connectedness may be a highly nonlinear phenomenon, and time-varying parameters are an important way to allow for nonlinearity. Indeed as "White's theorem" makes clear (see Granger (2008)), linear models with time-varying parameters are actually very general approximations to arbitrary nonlinear models.

Econometric methods for models with time-varying parameters (including VARs and DFMs) are well known, and state space representations and Gaussian maximum-likelihood estimation via the Kalman filter are immediate.[15] Random-walk parameters may be a natural specification, in which case a zero innovation variance corresponds to constant parameters. One can even have factor structure in the evolution of the parameters themselves, as in Stevanovic (2010).

The advantage of explicitly time-varying parameters is that, under adequate specification of the approximating model, it affords optimal inference regarding the existence and degree of parameter variation. The disadvantage is that, under significant misspecification of the approximating model, all bets are off.

Rolling-Sample Estimation

Alternatively, one can capture parameter variation by using a rolling estimation window; we write $\hat{C}(x, H, \widehat{M}(\theta; w))$, where w denotes window width. We then estimate the model repeatedly, at each time using only the most recent w observations.

The advantages of this approach are its tremendous simplicity and its coherence with a wide variety of possible data-generating processes (DGPs) involving

[15] See, for example, Harvey (1991).

time-varying parameters. The disadvantages are that given a particular DGP it is generally suboptimal, and it requires selection of w. Too large a w produces "oversmoothing," and too small a w produces "undersmoothing," in a manner precisely analogous to bandwidth choice in density estimation.

There are several issues related to window shape. First, the uniform window described above is one-sided. One-sided windows enable real-time analysis, but they produce a phase shift relative to two-sided symmetric windows. At least for off-line analysis, one may want to consider two-sided (presumably symmetric) windows.

Second, one may want to weight nearby observations more heavily than distant observations. In one-sided estimation, for example, we may want to weight the recent past more heavily than the distant past, as for example with exponential smoothing.[16] In that context, one must choose a smoothing weight rather than a window width.

Discussion

Here we address several remaining issues.

Pruning and Shrinkage

A VAR(p) may be selected using the standard information criteria, and inference for the remaining VAR coefficients (or variance decompositions) may be achieved using asymptotics, bootstrap, and so on. In addition, thresholding measures may be introduced to prune insignificant VAR coefficients.

"Soft thresholding" may prove especially valuable. In particular, following a long "Minnesota prior" tradition in the VAR literature, it will likely prove helpful to shrink log prices, log volatilities, and fundamentals toward a vector random walk.[17] Particularly in the rolling-sample estimation that we will use extensively, degrees of freedom can be rather limited, so the incorporation of prior information in addition to likelihood information is appealing.

Note that even if we prune insignificant VAR coefficients, all of the pairwise directional connectedness measures will still generally be nonzero, although some may be small. Hence size and/or significance thresholding might be beneficially applied not to the VAR coefficients, but rather directly to the pairwise connections. Most real-world networks are directional, weighted, and sparse, and direct pruning of pairwise connections helps maintain sparseness in our estimated networks.

[16] Such strategies are successfully implemented by Boudoukh et al. (1998) in the related but different context of volatility estimation.

[17] Note that log *prices*, not returns, are shrunken toward a vector random walk. This shrinks returns toward vector white noise.

Abrupt Parameter Variation

Both the truly time-varying parameter and rolling regression approaches as introduced thus far imply smoothly varying coefficient variation (and hence smoothly varying connectedness), whereas real-world variation might sometimes be abrupt, as with a sharp switch into a crisis regime. This world view might lead one to favor the truly time-varying parameter approach, because, for example, one could introduce Markov switching there. The rolling window approach, in contrast, necessarily smooths significantly unless one chooses a very small bandwidth, which can be problematic for other reasons. Nevertheless, the stark simplicity of the rolling window approach is so appealing, and its results are generally so intuitive and informative, that we adopt it in much of what follows.

Spurious Variation in Connectedness

Many authors have discussed the fact that apparently time-varying conditional correlation could simply be a spurious artifact of time-varying volatility. That is, put roughly, correlation and variance are themselves positively correlated, so correlation must be higher when variance is high.

Although obvious, the insight that variation and covariation are themselves positively correlated is nevertheless easily forgotten. Recent financial econometric awareness evidently traces to a 1995 NBER conference discussion of Karolyi and Stulz (1996) by Robert Stambaugh, as reported in Ronn et al. (2009). The basic stylized result is that if x and y are *iid* bivariate zero-mean Gaussian, then

$$corr(x, y \mid x^2 = a^2) = \left(\frac{1+\delta}{1+\delta\rho^2}\right)^{1/2} \rho,$$

where $\delta = (a^2 - \sigma_x^2)/\sigma_x^2$. As a grows, so too does δ, so $corr(x, y \mid x^2 = a^2) \to 1$. Awareness of this "Stambaugh effect" is very much evident, for example, in influential work such as Forbes and Rigobon (2002), who are careful to assess not just whether correlations rise in crises, but whether they rise by *more* than would be expected simply due to the Stambaugh effect.

One might wonder whether we have a similar "extremes bias" in estimating C using a rolling window, so that spuriously high C might be inferred during high-volatility times. We think not. We study a sophisticated measure of connectedness quite different from simple covariance or correlation, and our approach is actually very different from those subject to the Stambaugh effect. In particular, because our various connectedness measures are built from variance decompositions, they already control for total variation. That is, our measures track forecast error variance due to non-own shocks *relative* to total forecast-error variance.

Measurement Error

One might sometimes want to consider measurement error. Sometimes the x variables are more-or-less unambiguously measured, as with returns or GDPs (although even GDPs are just estimates). Other times the x variables may be trickier to interpret, as with, for example, financial analyses where x contains realized volatilities or global business cycle analyses where x contains country business conditions indexes.

When x is arguably measured with error, there is an issue as to whether to attempt to explicitly account for it. The crucial case for our purposes is when x is a vector of realized volatilities. One approach is to view realized volatility not as the direct object of interest, but rather as a (noisy) estimate of underlying quadratic variation. In that case, one might want to acknowledge measurement error explicitly, as proposed by Hansen and Lunde (2014). Doing so will generally increase the persistence of the estimated dynamics of x, which may affect variance decompositions and hence $\widehat{C}_t(x, H, \widehat{M}_{1:T}(\hat{\theta}_t))$.

Another approach is simply to treat realized volatility as the object of direct interest, rather than as an estimator subject to sampling error (see also Andersen et al. (2003)). Realized volatility—not underlying quadratic variation or any other object that realized volatility may or may not be construed as estimating—is, after all, directly traded in the volatility swap markets. We generally take this latter approach.

1.4 ON THE CONNECTEDNESS OF CONNECTEDNESS

Although our approach to connectedness measurement is hopefully novel, we hasten to add that we are hardly the first to think about connectedness. In this section we relate and contrast our approach to others that have appeared. We find it useful and instructive to first compare various measures proposed in the financial econometrics literature, then compare the network literature, and finally compare the international finance and macro literature.

1.4.1 Financial Econometric Connectedness

The finance literature has long focused on connectedness of various sorts. Here we highlight two varieties, one ancient (correlation-based) and one modern (extremes-based).

We begin with correlation-based approaches. One might suspect that correlation is unlikely to be able to address our concerns, as it measures only linear, nondirectional, pairwise association—and that suspicion is largely correct. Nevertheless, correlation is of some value, and it features prominently in several developments closely related to our concerns. We then move to extremes-based approaches, examining how market tail risk varies with the activities of a single firm.

Correlation Measures

Correlation is an obvious measure of certain aspects of connectedness. It measures only linear dependence, but some nonlinearities can be accommodated by moving to a conditional perspective, with time-varying correlations. A huge literature on multivariate volatility modeling focuses on conditional correlation, as described for example in Taylor (2007). An important recent example is the dynamic conditional correlation (DCC) model of Engle (2009), which builds on earlier work by Bollerslev (1990). Related earlier work also includes that in the "Meteor Showers or Heat Waves?" tradition of Engle et al. (1990).[18] Also related is the market-based implied correlation "contingent claims" approach; see, for example, Gray and Malone (2008) and many of the references therein.

Correlation is also nondirectional, as $corr(x, y) = corr(y, x)$. This contrasts with our notion of pairwise directional connectedness.[19]

Finally, correlation is only a pairwise measure of association. We often want to move beyond pairwise connections, exploring in a nondirectional way the connectedness of all firms or markets (total connectedness in our jargon). Certain recent proposals push in that direction and are therefore related to our notions of total connectedness. For example, the equicorrelation of Engle and Kelly (2012) averages across all pairwise correlations, clearly addressing a certain aspect of total connectedness.

We are often interested in questions that are non-pairwise, yet directional, like "How connected is one firm to all others?" (total directional connectedness in our jargon). Certain recent proposals push in that direction and are therefore related to our notion of total directional connectedness. We turn to them now.

[18] Examples include Edwards and Susmel (2001), Edwards and Susmel (2003), Bekaert and Harvey (1995), Ng (2000), Bekaert et al. (2005), and Baele (2009). For additional references see Gaspar (2012).

[19] Interestingly, some recent approaches have both a correlation flavor and some notion of directionality, as with the mutually exciting jump processes of Aït-Sahalia et al. (2010) and the associated notion of "co-jumping."

Systemic Measures: *CoVaR* and *MES*

Correlation is extreme in a sense, in that it only tracks pairwise connectedness. Certain recently proposed measures go to the other extreme, tracking market-wide systemic risk. Correlation is still featured, but instead of correlation between two firms (say), the focus is on correlation between a firm and the overall market. In addition, the new measures tend to focus on extreme ("tail") events, featuring, for example, quantities like expected shortfall (expected loss, conditional upon loss exceeding a distress threshold).

The *CoVaR* of firm (bank, ...) F, "$CoVaR(F)$," introduced by Adrian and Brunnermeier (2011), is overall market value at risk (VaR) given that firm F is under distress (i.e., firm F has a VaR loss). They propose to measure F's contribution to systemic risk as the difference between $CoVaR(F)$ and market VaR when F is in its median state. Effectively, then, the *CoVaR* approach measures systemic risk of F as the derivative of market VaR with respect to firm F distress.

Related to *CoVaR*, but distinct, is the marginal expected shortfall (*MES*) of Acharya et al. (2010) and Brownlees and Engle (2012),

$$S^{e\prime}_{i,t-1}(c) = \frac{\partial S^e_{i,t-1}(c)}{\partial w_i} = -E_{t-1}(r_{it}|r_{mt} < c),$$

where expected market shortfall is

$$S^e_{t-1}(c) = -E_{t-1}(r_{mt}|r_{mt} < c)$$

and w_i is the weight of firm i in the market,

$$r_{mt} = \sum_{i \in I} w_i r_{it}.$$

The question asked and answered by *MES* is simple and intuitive: If firm F were to get a little bigger relative to its peers, how would that affect expected market shortfall? That is, the systemic risk of F is measured as the derivative of market expected shortfall with respect to firm size.

Both *CoVaR* and *MES*, at least as typically interpreted, are similar in spirit to our measures of total directional connectedness (from firm F to all others). In addition, although they are static measures as stated, they can be made dynamic by rolling the estimation or by taking an explicitly time-varying volatility perspective.

1.4.2 Network Connectedness

Networks are everywhere in modern life, from power grids to Facebook. Not surprisingly, research on networks has grown explosively in recent years. Newman (2010) provides a masterful general introduction, and Jackson (2008) and Easley and Kleinberg (2010) provide good insights into associated economic issues.

Once one starts thinking about networks, one is naturally led to think about network connectedness. What is connected? Which connections are direct, and which are indirect? How *strong* are various connections? And first, of course, we must confront deep questions. Just what *is* network connectedness? How might we define it? Is it a pairwise or system-wide concept, or both, or neither? How might it be related to the notion of connectedness that we have thus far emphasized, based on variance decompositions? Given an acceptable definition of network connectedness in theory, can we *estimate* it in practice from real data? Is connectedness evolving, and, if so, how quickly and with what patterns?

Interestingly, it turns out that our connectedness measures, originally derived independently of the network literature, are closely related to several measures commonly used to describe network topology. As we shall soon see in detail, the variance decomposition of a vector autoregression defines a network.

A network is composed of N nodes and L links, or connections, between nodes. Ultimately a network is simply an $N \times N$ adjacency matrix A of zeros and ones,

$$A = (a_{ij}), \tag{1.1}$$

where $a_{ij} = 1$ if nodes i and j are connected, and $a_{ij} = 0$ otherwise. Note that A is symmetric, because if i and j are connected, then so too must be j and i. It is no accident that we gave the seemingly trivial equation (1.1) an elevated status, separating it from the text and giving it its own number. Mathematically, the adjacency matrix A *is* the network, and all network properties are embedded in A.

Assessing network connectedness and other properties is challenging, however, and there is no single, all-encompassing measure. The only thing that's all-encompassing is the matrix A itself, yet staring at a 500×500 A matrix (for example) is not likely to be revealing. Hence we analyze A in various complementary ways. Most of the descriptive measures of network topology that are useful for our purposes fall into one of two key families associated with one node (e.g., degree, which we define shortly) or two nodes (e.g., distance, which we also define shortly).[20] In what follows we focus on

[20] We could continue. For example, three-node measures (e.g., transitivity) can capture clustering phenomena, but they are not of central importance for our purposes.

degree, distance, and a third interesting network topology measure associated with *all* nodes, the second smallest Laplacian eigenvalue.[21]

The Degree Distribution

A node's *degree* is its number of links to other nodes, which summarizes certain aspects of the connectedness of the node. Immediately the degree of node i is

$$d_i = \sum_{j=1}^{N} A_{ij}$$

Degree is a single-node property, but we can of course examine the pattern of degrees across nodes. The *degree distribution* is the probability distribution of degrees across nodes. The degree distribution has N points of support and can be viewed as a univariate distribution. It summarizes certain aspects of the connectedness of the entire network. Important aspects include its location, scale, skewness, and tail thickness.

Location and Scale

Global connectedness considerations suggest examining the location of the degree distribution. Hence an obvious and standard measure of network connectedness is the mean of the degree distribution (Newman, 2003). A high mean degree indicates high overall connectedness.[22]

If the degree distribution is asymmetric, perhaps with a long right tail due to a few outlying high-degree nodes, then the median may prove to be a more robust and reliable location measure. Related, we may want to examine dispersion of degrees around the mean (that is, examine degree scale in addition to location), as assessed for example by standard deviation or interquartile range.

Tail Thickness

The shape of the degree distribution governs many network properties. We have already mentioned the first three moments, linked to notions of location, scale, and asymmetry. Another important aspect of degree distribution shape is tail thickness, which is related to the fourth moment, or kurtosis.

[21] Good reviews and financial applications of network-theoretic connectedness measures include Bech and Atalay (2010), Adamic et al. (2010), and the references therein.

[22] One could also examine many aspects of the degree distribution beyond its moments, including "inequality" as measured by Gini coefficients or Herfendahl indexes. One could also examine stochastic dominance of degree distributions. We shall not pursue those issues here.

The binomial (or Poisson or Gaussian—see below) is one of two crucially important benchmark degree distributions. It governs the randomly formed networks ("random networks") pioneered by Erdős and Rényi (1959) a half-century ago, in which case

$$P(d) = \binom{N-1}{d}\pi^d(1-\pi)^{N-1},$$

where π is the link-formation probability. For large N and small π, the usual Poisson distribution holds, $P(d) = e^{-(N-1)\pi}((N-1)\pi)^d/d!$. Similarly, for large N and fixed π the Gaussian distribution holds. The key feature of the Gaussian is its "thin tails," which decay exponentially quickly. This makes nodes with extremely large degree extremely unlikely.

The second crucially important benchmark degree distribution has tails governed by the power law:

$$P(d) \propto d^{-\lambda}.$$

Power law distributions are *scale-free* in that $\frac{P(d_1)}{P(d_2)} = \frac{P(cd_1)}{P(cd_2)}$, $\forall\, c$; and in contrast to the quickly decaying tails of Gaussian distributions, power-law distributions have slowly (hyperbolically) decaying tails. Equivalently, power-law degree distributions are log-linear in the tails, $\log(P(d)) = c - \lambda \log(d)$. The "fat tails" associated with power law degree distributions tend to produce huge-degree nodes, sometimes called hubs.

The tension between Gaussian (thin-tailed) and power-law (fat-tailed) distributions is a key theme in modern asymptotic statistical theory. Under very general conditions, the large-sample distributions of appropriately standardized sums are members of the stable family, but the stable family spans both Gaussian and power-law distributions.[23] The classic Gaussian and power-law benchmarks arise theoretically under certain conditions, and one or the other often appears to accord with observation, but the degree distribution—Gaussian, power-law, or something else—for any particular network is ultimately a purely empirical and situation-specific matter.

The Distance Distribution

Associated with every pair of nodes is a *distance*, the length of shortest path connecting them.[24] The probability distribution of all such distances is called the *distance*

[23] See, for example, Embrechts et al. (1997) and the references therein for rigorous scientific development, and see Taleb (2007) for popular exposition.

[24] We implicitly assume a connected network, meaning that at least one path, and hence a shortest path, exists between any node pair.

distribution. As with degrees and the degree distribution, distances and the distance distribution summarize certain aspects of connectedness—different from those captured by degree, and neither more nor less important, just different.

Empirically, mean or maximum distance is usually very small in economic networks and in all networks, even huge networks. This fact is memorably enshrined in the "six degrees of separation" and "small-world" phenomena.[25]

Theoretically, and closely related, it is now well known that, under assumptions, only k steps are needed to reach N nodes, where

$$k = \frac{\log(N)}{\log(E(d))}. \tag{1.2}$$

The small-world phenomenon is embedded in the $\log(N)$ term, as the required number of steps grows with the log of N—that is, only very slowly with N. Note also the explicit role of mean degree in the denominator: The larger the mean degree, the smaller the expected number of steps. Indeed equation (1.2) provides fundamental insight into the relationships among distance, degree, and network size.

Note that distance is a two-node property.[26] Like the degree distribution, the distance distribution has N points of support and can be viewed as a univariate distribution. The mean of the distance distribution ("mean distance") provides additional perspective on connectedness, as does the maximum distance, which is often called the network *diameter*. To the best of our knowledge, simple approximate characterizations like Gaussian and power-law have not been theoretically derived or empirically observed, and hence are not routinely advocated, for distance distributions.

The Second Laplacian Eigenvalue

Another, rather different (or so it seems) network connectivity measure is closely related to our interests. Jadbabaie et al. (2002) show that an overall measure of

[25] "Six degrees of separation" refers to how exceedingly rare it is for paths between nodes to be of length greater than six. Hence networks are "small worlds." See Watts and Strogatz (1998).

[26] We could go even farther, measuring, for example, three-node transitivity of links ("clustering") as follows. We ask: If i is connected to k, and if j is also connected to k, then is it more likely than otherwise that i is connected to j? We measure transitivity at node k as the fraction of ij connections, where both i and j are connected to k: $\frac{\Sigma_{ij} I(ij)}{\binom{d_k}{2}}$, where $I(\cdot)$ is the indicator function, and the sum is over all ij links such that i is connected to k and j is connected to k. (The denominator is just the number of such ij pairs.) Because transitivity is a three-node property, the transitivity distribution has $O(N^3)$ points of support and can be viewed as a trivariate distribution. One could presumably continue defining n-node connectivity measures for $n > 3$. But even clustering ($n = 3$) is getting rather far from our central interest of overall network connectivity.

connectivity ("algebraic connectivity") is given by the second smallest Laplacian eigenvalue.[27] We refer to it simply as the "Laplacian eigenvalue." The $N \times N$ Laplacian matrix is

$$L = D - A,$$

where D is a diagonal matrix containing the node degrees and A is the adjacency matrix defined earlier in equation (1.1). As discussed by Kolaczyk (2010), the larger the second smallest Laplacian eigenvalue, λ_2, the more difficult it is to separate a network into disconnected sub-networks by eliminating a few links.

Variance Decompositions as Networks

A fundamental insight is that a variance decomposition matrix D *is* a network adjacency matrix A. Hence variance decompositions define networks, and network connectedness measures may be used in conjunction with variance decompositions of a set of variables x to understand the nature of connectedness among the components of x.

The networks defined by variance decompositions, however, are rather more sophisticated than the classical network structures sketched thus far. First, the links are not simply 0 or 1; rather, they are *weighted,* with some strong, and others weak. Second, they are *directed*; that is, the strength of the ij link is not necessarily the same as the strength of the ji link, so the adjacency matrix is not necessarily diagonal. Finally, they are *dynamic,* so that the link weights may change over time.

Weighted, directed, dynamic versions of all network statistics are readily defined. Our degrees are obtained not by summing zeros and ones, but rather by summing the pairwise weights, and there are now "to" degrees and "from" degrees (in-degrees and out-degrees in the more standard jargon).

Two key insights emerge readily. First, our total directional connectedness measures are precisely node in-degree and out-degree. Second, our total connectedness measure is simply the mean degree (to or from—it's the same either way). Other network statistics such as the mean distance and Laplacian eigenvalue complement the degree-based measures.

Our approach is quite different from attempting to use estimated VAR coefficients or causal patterns to define networks directly, as in Dahlhaus and Eichler (2003), Bilio et al. (2012), and Shojaie and Michailidis (2010), who study Granger-causal connections.

[27] The smallest Laplacian eigenvalue is 0 by construction, so it is of no interest.

1.4.3 "Spillover" and "Contagion" Connectedness

Parts of the international finance literature are also related to our vision of connectedness, although they are also distinct. Insightful reviews include Claessens and Forbes (2001), Dungey et al. (2011), and Dungey et al. (2005). In those reviews, much discussion and many models are devoted to concepts and words like "spillovers," "contagion," "herd behavior," and the like. Forbes and Warnock (2012) even attempt to define separate "surge," "stop," "flight," and "retrenchment" episodes.

Confusingly, however, such terms mean different things to different people. Authors like Dungey et al. (2011), for example, use "contagion" to mean increased contemporaneous correlations during crises, coming from increased correlations among idiosyncratic shocks. Such contagion is sometimes also called "pure contagion," in contrast to "fundamentals-based" contagion, which refers to increased reliance on underlying common factors. In yet another contrast, authors such as Demiris et al. (2014) use contagion to mean literal step-by-step transmission, as when flu spreads sequentially from one person to another.

Dungey and Martin (2007) and Dungey et al. (2011) provide an important unifying perspective, arguing that most of the literature fits under the broad umbrella of factor models. This is especially interesting because of the balkanized nature of much of the literature, as evidenced, for example, by the correlation-based approach of Forbes and Rigobon (2002), the VAR approach of Favero and Giavazzi (2002), the probability-modeling approach of Eichengreen et al. (1995) and Eichengreen et al. (1996), and the multivariate extreme-value approach of Bae et al. (2003).

A simple one-factor model, as in Dungey et al. (2011), is

$$y_t = \lambda F_t + \varepsilon_t,$$

where the common factor F_t may or may not be serially correlated (i.e., we may be in a dynamic or static factor environment), depending on the situation and the idiosyncratic factors (shocks) $\varepsilon_t \sim (0, \Sigma)$.[28] The factor model provides a precise and rich environment in which one can attempt to disentangle episodes of high co-movement into those due to large common factor movements, increased loadings on common factors, increased idiosyncratic shock correlations, and flu-like contagion transmission with lagged shocks in one market affecting current conditions in another. For example, one might view a certain type of contagion as synonymous with diagonal Σ during "normal" times and nondiagonal Σ during "crisis" times. Hence, given an assumed crisis chronology and a number of other maintained assumptions, one can investigate contagion by testing whether Σ shifts from diagonal to nondiagonal during crises.

[28] As regards possible serial correlation in the common factor F_t, if y_t is a return, then there is little need to allow for it, whereas if y_t is a return volatility, then there is likely a strong need.

There are several points of distinction between our approach and that of Dungey et al. (2011). First, their emphasis is mostly on testing, whereas ours is more on measurement and estimation. Second, their approach has a strong ex post flavor requiring knowledge of crisis periods, which is difficult in real time, whereas our framework is more amenable to real-time analysis. Third, and related, their conception of time-varying connectedness is rather rigid, corresponding to structural shifts between crisis and non-crisis periods, whereas ours is flexible. Fourth, their framework is based on statistical factor analysis, whereas ours is effectively based on modern network theory.

1.4.4 Concluding Remarks

In this section we have compared our connectedness measures to a variety of others. Interestingly, the closest connections [sic] are to classical measures of network topology. There are a number of related developments and points of contrast to the classical network literature. As we have stressed, the variance decomposition networks to which we are naturally led are directed, weighted, and dynamic. Moreover, the weights (variance decompositions) are *estimated* from samples of data, typically from "small data" rather than "big data," in the sense of Diebold (2003). There are two layers of dynamics: The VAR model is of course dynamic, and moreover its parameters are time-varying. Our approach effectively marries VAR variance-decomposition theory and network topology theory, recognizing that variance decompositions of VARs form networks and also characterizing connectedness in those variance decomposition networks, which in turn characterizes connectedness of the variables in the VAR.

2

U.S. ASSET CLASSES

Financial crises occur with notable regularity; moreover, they display notable similarities (e.g., Reinhart and Rogoff (2008)). During crises, for example, financial market volatility generally increases sharply and generates connectedness across markets. One would naturally like to be able to measure and monitor such volatility connectedness, both to provide "early warning systems" for emergent crises and to track the progress of extant crises.

Motivated by such considerations, Diebold and Yilmaz (2009) introduce a volatility connectedness measure based on forecast error variance decompositions from vector autoregressions (VARs).[1] It can be used to measure connectedness in returns or return volatilities (or, for that matter, any return characteristic of interest) across individual assets, asset portfolios, asset markets, and so on, both within and across countries, revealing connectedness trends, cycles, bursts, and so on. In addition, although it conveys useful information, it nevertheless sidesteps the contentious issues associated with the definition and existence of episodes of "contagion" or "herd behavior."[2]

[1] VAR variance decompositions, introduced by Sims (1980), record how much of the H-step-ahead forecast error variance of some variable, i, is due to innovations in another variable, j.

[2] On contagion (or lack thereof) see, for example, Forbes and Rigobon (2002).

However, the framework as presently developed and implemented has several limitations, both methodological and substantive. Consider the methodological side. First, Diebold and Yilmaz (2009) rely on Cholesky-factor identification of VARs, so the resulting variance decompositions are useful to generate and analyze *total* connectedness (from/to each market *i*, to/from all other markets, added across *i*) measures. One would also like to examine *directional* connectedness (from/to a particular market).

Now consider the substantive side. Diebold and Yilmaz (2009) consider only the measurement of connectedness across identical assets (equities) in different countries. But various other possibilities are also of interest, including individual-asset connectedness within countries (e.g., among the 30 Dow Jones Industrials in the United States) and across asset classes (e.g., between stock and bond markets in the United States) and of course various blends. Connectedness across asset classes, in particular, is of key interest given the recent global financial crisis (which appears to have started in credit markets but was transmitted to equities), but it has not yet been investigated in the Diebold–Yilmaz framework.

Here we fill these methodological and substantive gaps. We use a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to variable ordering, and we explicitly include directional volatility connectedness. We then use our methods in a substantive empirical analysis of daily volatility connectedness across U.S. stock, bond, foreign exchange, and commodities markets over a 10-year period, including the recent global financial crisis. This is of particular interest because connectedness across asset classes may be an important aspect of the global financial crisis that began in 2007.

We proceed as follows. We begin by describing our data in the next section. Then we calculate total volatility connectedness in Section 2.2. We then analyze the dynamics of volatility connectedness, examining rolling-sample total connectedness, rolling-sample directional connectedness, rolling-sample net directional connectedness, and rolling-sample net pairwise connectedness in Section 2.3.

2.1 VOLATILITY IN U.S. ASSET MARKETS

We examine daily volatilities of returns on U.S. stock, bond, foreign exchange, and commodity markets. In particular, we examine the S&P 500 index, the 10-year Treasury bond yield, the New York Board of Trade U.S. dollar index futures, and the Dow-Jones/UBS commodity index.[3] The data cover the period from January 25, 1999 through June 28, 2013, for a total of 3630 daily observations.

[3] The DJ/AIG commodity index was re-branded as the DJ/UBS commodity index following the acquisition of AIG Financial Products Corp. by UBS Securities LLC on May 6, 2009.

We assume that volatility is fixed within a day but variable across periods. Following from this assumption in our analyses of volatility connectedness throughout the book, we rely either on the daily realized volatility (as in Chapter 3) or on the daily range estimates of volatility (as in Chapters 2, 4, 5, 6, and 7).

In the tradition of a large literature dating at least to 1980, we calculate the range volatility estimate using daily high (maximum), low (minimum), opening, and closing prices à la Garman and Klass (1980). When we do not have the opening and closing prices for at least one asset, we estimate daily variance of all assets using daily high and low prices only, following the formula proposed by Parkinson (1980)[4]:

$$\tilde{\sigma}_p^2 = 0.361\,(h - l)^2,$$

where h and l are the natural logarithms of the daily high and low prices of the asset in question. Because $\tilde{\sigma}_p^2$ is an estimator of the daily return variance, the corresponding estimate of the annualized daily percentage standard deviation (volatility) is $\hat{\sigma}_p = 100\sqrt{365 \cdot \tilde{\sigma}_p^2}$. We plot the four assets' daily return volatilities in Figure 2.1

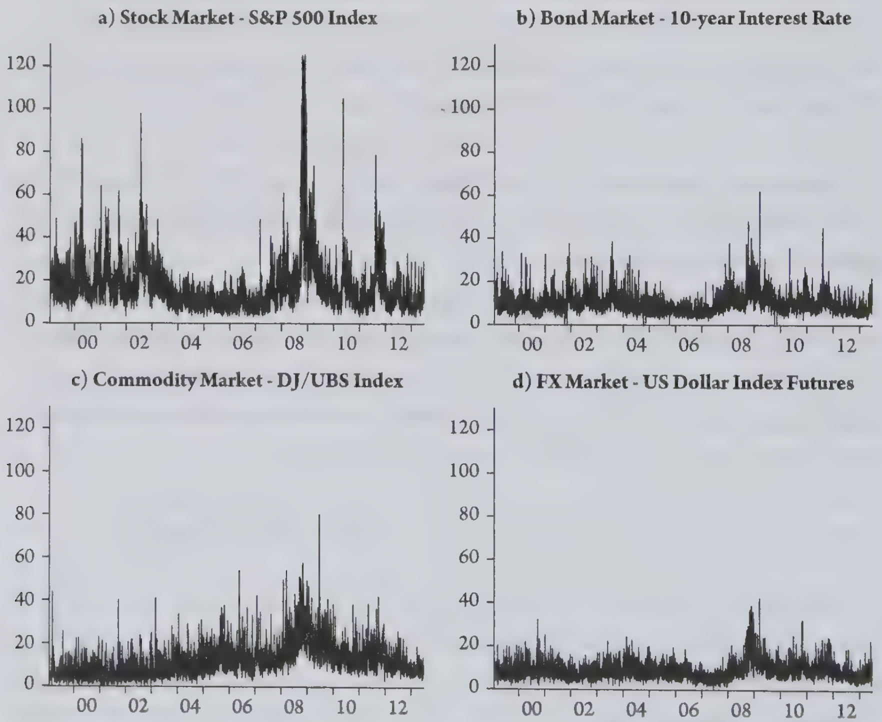


Figure 2.1 Daily U.S. financial market volatilities (annualized standard deviation, percent).

[4] For background, see Alizadeh et al. (2002) and the references therein.

Table 2.1 Summary Statistics: Log of Annualized Asset Return Volatilities

	Stocks	*Bonds*	*Commodities*	*FX*
Mean	2.664	2.187	2.258	2.073
Median	2.645	2.179	2.34	2.082
Maximum	4.83	4.122	4.383	3.746
Minimum	1.01	–3.411	–1.609	–0.877
Std. dev.[a]	0.586	0.49	0.709	0.474
Skewness	0.244	–0.743	–0.842	–0.206
Kurtosis	3.174	10.41	4.827	3.794

[a] Std. dev., standard deviation.

and we provide summary statistics of log annualized volatility in Table 2.1. Several interesting facts emerge:

1. The stock market has been the most volatile, followed by commodity market, while bond and FX markets were comparatively more tranquil.
2. Volatility dynamics appear highly persistent, in keeping with a large literature summarized, for example, in Andersen et al. (2006a).
3. All volatilities are high during the recent global financial crisis of 2007–2009, with stock and commodity market volatility, in particular, displaying huge jumps.
4. Volatilities continued to stay high in 2010 and in the second half of 2011, due to the Greek, and, later, the eurozone sovereign debt crisis.

Throughout the sample, the stock market went through at least three periods of major volatility. In 1999, daily stock market volatility was close to 25%, but it increased significantly to above 25% and fluctuated around that level until mid-2003, moving occasionally above 50%. After mid-2003, it declined to less than 25% and stayed there until August 2007. From August 2007 to June 2009, stock market volatility reflected the dynamics of the sub-prime crisis and the ensuing global financial crisis. After a brief respite from June 2009 to December 2009, stock market volatility rose sharply in the first half of 2010 as the markets anxiously waited for the Eurozone leaders to produce a solution to the Greek debt crisis. Stock market volatility increased once again as the Greek debt crisis spread to other countries in the eurozone.

In the first half of our sample, daily bond return volatility was lower than the stock market return volatility. While it was lower than 20% for most of 2000, in the first and last few months of 2001, it increased and fluctuated between 25% and 40%. Bond market volatility remained around 25% until the end of 2004 and fluctuated around 10–15% from late 2005 through the first half of 2007. Since August 2007, volatility in bond markets has also increased significantly during the global financial crisis. Although it increased in several instances in 2010 through 2013, in each case the volatility of daily bond returns declined and fell below 20%.

Commodity market volatility used to be lower compared to stock and bond markets, but it has increased slightly over time, especially in 2005–2006, in 2008 and early 2009, and in mid-2010 through mid-2012. FX market volatility has been the lowest among the four markets. It increased in 2008 and moved to a 25–40% band following the collapse of Lehman Brothers in September 2008. As was the case in other markets, FX market volatility declined in the second half of 2009, only to increase slightly again in 2010 and 2011.

2.2 UNCONDITIONAL PATTERNS: FULL-SAMPLE VOLATILITY CONNECTEDNESS

Table 2.2 is the volatility connectedness table for the four asset classes obtained through generalized variance decomposition as discussed in Section 1.3. Its *ij*th entry is the estimated contribution to the forecast error variance of market *i* coming from innovations to market *j*. Hence the off-diagonal column sums or row sums are the directional connectedness "to others" and "from others," and the difference between the "to others" and "from others" is the "net" directional connectedness. In addition, the total volatility connectedness index appears in the lower right corner of the connectedness table. It is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals), expressed in percentage terms.[5] The volatility connectedness table provides an approximate "input–output" decomposition of the total volatility connectedness index.

The volatility connectedness table (Table 2.2) is based on vector autoregressions of order 3 and generalized variance decompositions of 12-day-ahead volatility forecast errors. Table 2.2 shows that all pairwise as well as the "to" and "from" total directional connectedness measures are statistically significant at the 1% or 5% level. The "net" total directional connectedness measures for the commodity and FX market return volatilities are not significantly different from zero.

In order not to clutter the connectedness table with standard errors, we present the volatility connectedness table in Table 2.A.1 again, with the corresponding

[5] As we have already discussed in Section 1.3, the approximate nature of the claim stems from the properties of the generalized variance decomposition. With Cholesky-factor identification the claim would be exact rather than approximate; see also Diebold and Yilmaz (2009).

Table 2.2 Volatility Connectedness Table, Four U.S. Asset Classes

	Stocks	*Bonds*	*Commodities*	*FX*	*FROM*
Stocks	83.8	11.1	0.7	4.4	16.2
Bonds	15.3	75.6	1.1	8.0	24.4
Commodities	0.9	0.9	95.0	3.2	5.0
FX	7.2	7.9	3.1	81.8	18.2
TO	23.4	19.9	4.9	15.6	
NET	7.2	−4.5	<u>−0.1</u>	<u>−2.6</u>	**15.9**

Notes: The sample is January 25, 1999 through June 28, 2013. Obtained from a VAR model of order 3, through generalized variance decompositions with a 12-day forecast horizon. Each cell in the 4 × 4 matrix section of the table reports the relative (in percentage terms) contribution of the "column" asset return volatility shocks to the variance of the forecast error for the "row" asset return volatility. Each cell in the directional "FROM" others column reports the total variance (of the forecast error) share attributable to other assets. Each cell in the directional "TO" others row reports the sum of the contributions of each asset to all other assets' variance of forecast errors. The "NET" directional connectedness row reports the difference between the corresponding cells in the "TO" row and the "FROM" column. The *total connectedness index*, the bold number in the lower right corner of the table, is equal to the average of the elements of the "FROM" column (similarly, the "TO" row). All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in the appendix to this chapter, in Table 2.A.1.

standard errors. The standard errors are derived from 5000 nonparametric bootstrap resamplings of the VAR error terms.[6]

Consider first what we learn from the table about directional connectedness (gross and net). In the "connectedness to others" row, we see that the gross directional volatility connectedness of three of the four markets to others ("to" connectedness) are not very different from each. While the stock market has the highest "to" connectedness, the bond market has the highest connectedness from others ("from" connectedness). With 4.9% to connectedness and 5.0% from connectedness, the commodity market is the least-connected asset market in the United States in the full sample. The "to" connectedness of the stock market (23.4%) exceeds its "from" connectedness (16.2%) by 7.2%, making it the market with the highest net connectedness among the four U.S. asset markets. The bond and FX markets, on the other hand,

[6] We also obtained standard errors through the parametric bootstrap method. As they were not much different from the ones obtained with the nonparametric bootstrapped method, throughout the book we present only the ones obtained through the nonparametric method.

have negative (–4.5% and –2.6%) net connectedness, indicating that they are the net receivers of shocks from other asset markets.

Now consider the total (nondirectional) volatility connectedness, which is effectively a distillation of the various directional volatility connectedness into a single index. The total volatility connectedness appears in the lower right corner of Table 2.2, which indicates that on average, across our entire sample, just 15.9% of the volatility forecast error variance in all four markets is due to the connectedness of markets. The summary of Table 2.2 is simple: Both total and directional connectedness over the full sample period were quite low.

2.3 CONDITIONAL PATTERNS: CONDITIONING AND DYNAMICS OF VOLATILITY CONNECTEDNESS

2.3.1 Total Volatility Connectedness

Clearly, many changes took place during the years in our sample. Some are well described as a more or less continuous evolution, such as increased linkages among global financial markets and increased mobility of capital due to globalization, the move to electronic trading, and the rise of hedge funds. Others, however, may be better described as bursts that subsequently subsided.

Given this background of financial market evolution and turbulence, it seems unlikely that any single fixed-parameter model would apply over the entire sample. Hence, the full-sample connectedness table and connectedness index constructed earlier, although providing a useful summary of "average" volatility connectedness dynamics, likely miss potentially important secular and cyclical movements in connectedness. To address this issue, we now estimate volatility connectedness using 200-day rolling samples, and we assess the extent and the nature of variation in connectedness over time via the corresponding time series of connectedness indices, which we examine graphically in the so-called total connectedness plot of Figure 2.2.

In the appendix to this chapter, in Figure 2.A.1 we present the sensitivity of the results to the choice of the forecast horizon (6, 12, and 18 days) and the VAR order (1 day through 6 days). The graphs clearly show that the dynamic total volatility connectedness is robust to the choice of the forecast horizon as well as the choice of the VAR order.

Starting at a value slightly lower than 15% in the first window, the total volatility connectedness for most of the first half of our sample fluctuates between 10% and 20%. This is a period of relative tranquility in financial markets in the United States and worldwide. The behavior of the total volatility connectedness index in the second half of the sample differs significantly from the first half. The total volatility

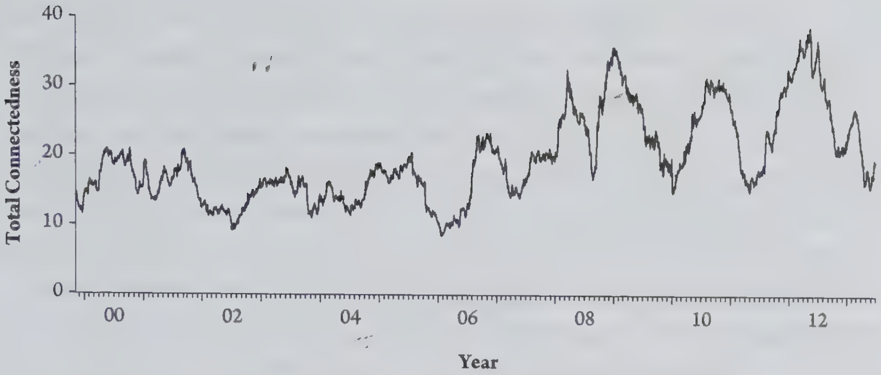


Figure 2.2 Total volatility connectedness, four U.S. asset classes (200-day window).

connectedness exceeds the 20% mark in mid-2006 and, most important, by far exceeds the 30% level during the global financial crisis of 2007–2009 and during the first (Greek debt crisis) and second phases of the Eurozone debt crisis since late 2009.

We can identify several cycles in the total connectedness plot. The first cycle started with the burst of the tech bubble in 2000, and the index climbed from 13% to 20%. In the second half of 2001 the index increased to 20% again, before dropping back to 10% at the end of January 2002. After hitting bottom in mid-2002, the index went through three relatively minor cycles until the end of 2005. The first cycle started in mid-2002 and lasted until the last quarter of 2003. The second cycle was shorter, starting in the first quarter of 2004 and ending in the third quarter. The third cycle during this period starts in the middle of 2004 and lasts until the end of 2005. All three cycles involve movements of the index between 10% and 20%.

After the rather calm era from 2003 through 2005, the connectedness index recorded a significant upward move in May through the end of 2006. On May 9, 2006 the Federal Open Market Committee (FOMC) of the Federal Reserve decided to increase the federal funds target rate from 4.75% to 5.00% and signaled the high likelihood of another increase at its June meeting.[7] After this decision the total volatility connectedness index increased from 12% at the end of April 2006 to 24% by November 2006. The fact that the Fed was continuing to tighten monetary policy led to an increase in volatility in the FX and bond markets, which increased the volatility connectedness from these markets to others.

Finally, the most interesting part of the total connectedness plot concerns the global financial crisis of 2007–2009 and the recent Eurozone debt crisis. One can see five volatility waves since 2007: July–August 2007 (credit crunch spread from

[7] Indeed, the FOMC increased the federal funds target rate to 5.25% at its June meeting and kept it at that level for more than a year until its September 2007 meeting.

the U.S. to European financial markets); January–March 2008 (panic in stock and foreign exchange markets followed by an unscheduled rate cut of three-quarters of a percentage point by the Federal Reserve and J.P. Morgan's takeover of Bear Stearns in March); September 2008–June 2009 (the collapse of Lehman Brothers, followed by full-blown panic in financial markets around the world that lasted until after the announcement of the results of the U.S. banks' stress tests in May 2009); throughout 2010 (the Greek debt crisis turned into a real headache for the EU as it engulfed Ireland and Portugal) and the second half of 2011 (Spain and Italy were caught in the whirlpool of the sovereign debt crisis and the ensuing systemic worries in the EU). The total volatility connectedness index surged all the way to 30–40% during the January–March 2008 and September 2008–June 2009 episodes of the U.S. financial crisis and also throughout 2010 and late 2011 as the Greek sovereign debt crisis turned into a eurozone-wide crisis. The total connectedness index increased slightly to around 25% in late 2012, as the December 31st deadline to increase the debt ceiling was fast approaching, while neither the Democrats nor the Republicans were willing to concede to avoid the so-called "fiscal cliff." Finally, the Fed's May and June announcements about the tapering of the Fed's $ 85 billion quantitative easing program in 2013 and 2014 generated only a slight upward move in the volatility connectedness.

2.3.2 Directional Volatility Connectedness

Thus far, we have discussed the *total* connectedness plot, which is of interest but disregards directional information. That information is contained in the "directional to others" row (the sum of which is given by $\tilde{C}^H_{\bullet\leftarrow i}$) and the "directional from others" column (the sum of which is given by $\tilde{C}^H_{i\leftarrow\bullet}$).

We now estimate the above-mentioned row and column of Table 2.2 dynamically, in a fashion precisely parallel to the total connectedness plot discussed earlier. We call these *directional* connectedness plots. In the top row of Figure 2.3, we present the "to" connectedness. As we discussed earlier, it is the directional volatility connectedness from each of the four asset classes *to others* and corresponds to the "directional to others" row in Table 2.2. In the middle row of Figure 2.3, we present the "from" connectedness. It is the directional volatility connectedness from others to each of the four asset classes and corresponds to the "directional from others" column in Table 2.2. Finally, in the bottom row of Figure 2.3 we present the "net" connectedness of each market as measured by the difference between its "to" and "from" connectedness.

Measures of directional connectedness vary greatly over time. During tranquil times, both the "to" and "from" connectedness of each market fluctuate between 10% and 20%, but during volatile times, directional connectedness to others increases all

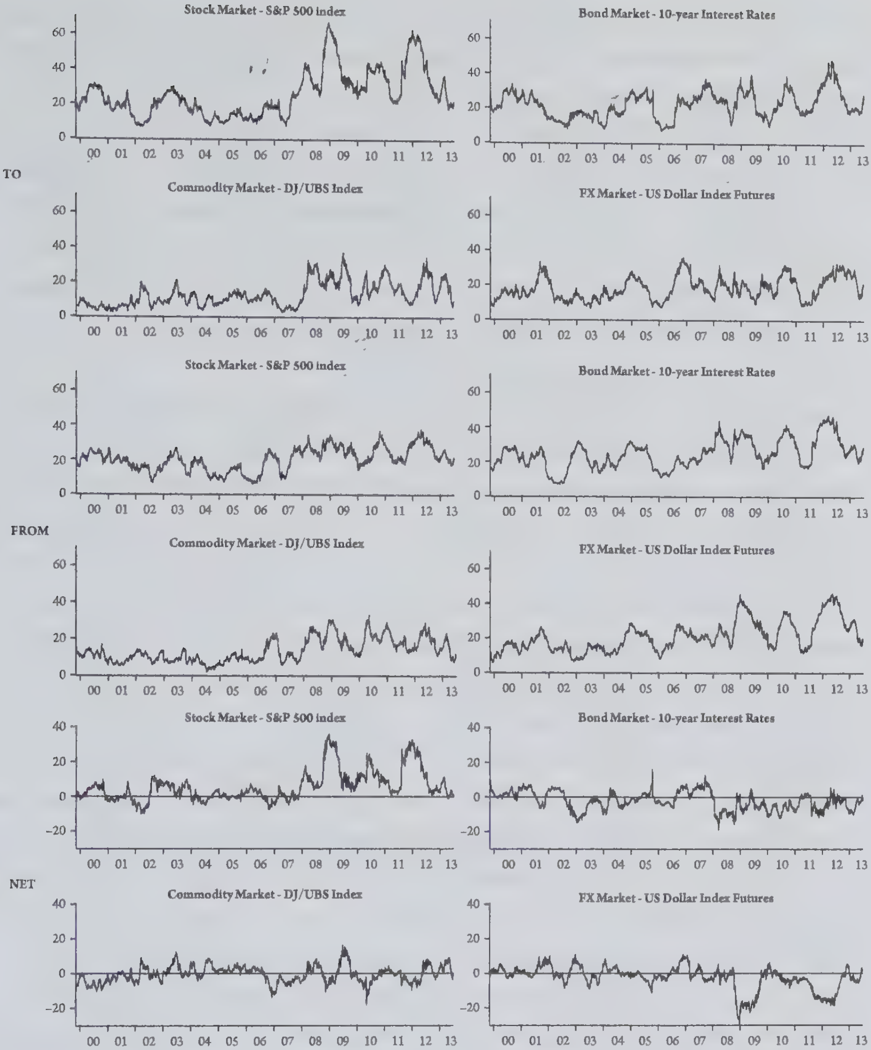


Figure 2.3 Total directional volatility connectedness, four U.S. asset classes (200-day window).

the way to 30% and above. Stock market connectedness to others increased to 40% in the first quarter of 2008 and during the Greek Debt crisis in 2010. It went up further to 60% following the bankruptcy of Lehman Brothers in September 2008 and in the summer of 2011, as Spain and Italy were caught in the whirlwind of the European sovereign debt and banking crisis.

The "to" connectedness of the U.S. bond, commodity, and FX markets also increased during the global financial crisis and the European debt crisis, but in general their levels of directional connectedness were lower than the ones attained by the U.S. stock market. The bond market tended to have higher "to" connectedness during the so-called "crisis era" than the commodity and FX markets. On the other hand, during the tranquil period of pre-2006, the "to" connectedness of the commodity markets was, in general, smaller than the "to" connectedness of the other three markets, fluctuating around 10%.

As with the "to" connectedness, the "from" connectedness varies noticeably over time. The relative variation pattern, however, is reversed, with "from" connectedness of the bonds and FX markets increasing relatively more in turbulent times. For example, during the January–March and September–December 2008 episodes and the euro crises of 2010 and 2011, the "from" connectedness of the bond and FX markets reached close to 45%–50%. The "from" connectedness of the stock and commodities markets, on the other hand, went up as high as 30%.

Above we discussed the "to" and "from" connectedness plots briefly, because our main focus is the net directional connectedness plot presented in the bottom row of Figure 2.3. We also present pairwise directional connectedness plots in Figure 2.4 and net pairwise directional connectedness plots between all possible pairs of markets in Figure 2.5.

Until the recent global financial crisis, "net" connectedness of the four markets never exceeded the 15% mark (see the bottom row of Figure 2.3). Furthermore, until 2007 all four markets were at both the giving and receiving ends of net volatility connectedness, with almost equal magnitudes. As might be expected, things have changed dramatically since January 2008. Net volatility connectedness from the stock market stayed positive throughout the several critical stages of the crisis, reaching as high as 40% after the collapse of Lehman Brothers in September 2008 and during the first and the second phases of the eurozone debt crisis. As of the end of December 2011, the net connectedness of the stock market was close to its all-time high value that was reached in 2008. The net connectedness plot for the stock market clearly reveals that the stock market acts as the market that reflects the news about the eurozone debt crisis. Increased volatility in the stock market due to developments in the eurozone sovereign debt crisis leads to an increase in the volatility connectedness of the stock market to other markets.

From 1999 to 2013, there were several major episodes of the "net" connectedness of the stock market to other markets (Figure 2.3): during 2000, from 2002 through the third quarter of 2003, in the second half of 2006, during the global financial crisis of 2007–2009, and during the eurozone debt crisis of 2010–2011. The first wave of high net volatility connectedness of the stock market followed the burst of the technology bubble in 2000. As the troubles of technology stocks intensified after March 2000, the "to" connectedness of the stock market increased above 30% in the second through the last quarter of 2000 (Figure 2.3). At the time, the bulk of the net volatility connectedness of the stock market was to the bond market and then to the commodities market (Figure 2.5).

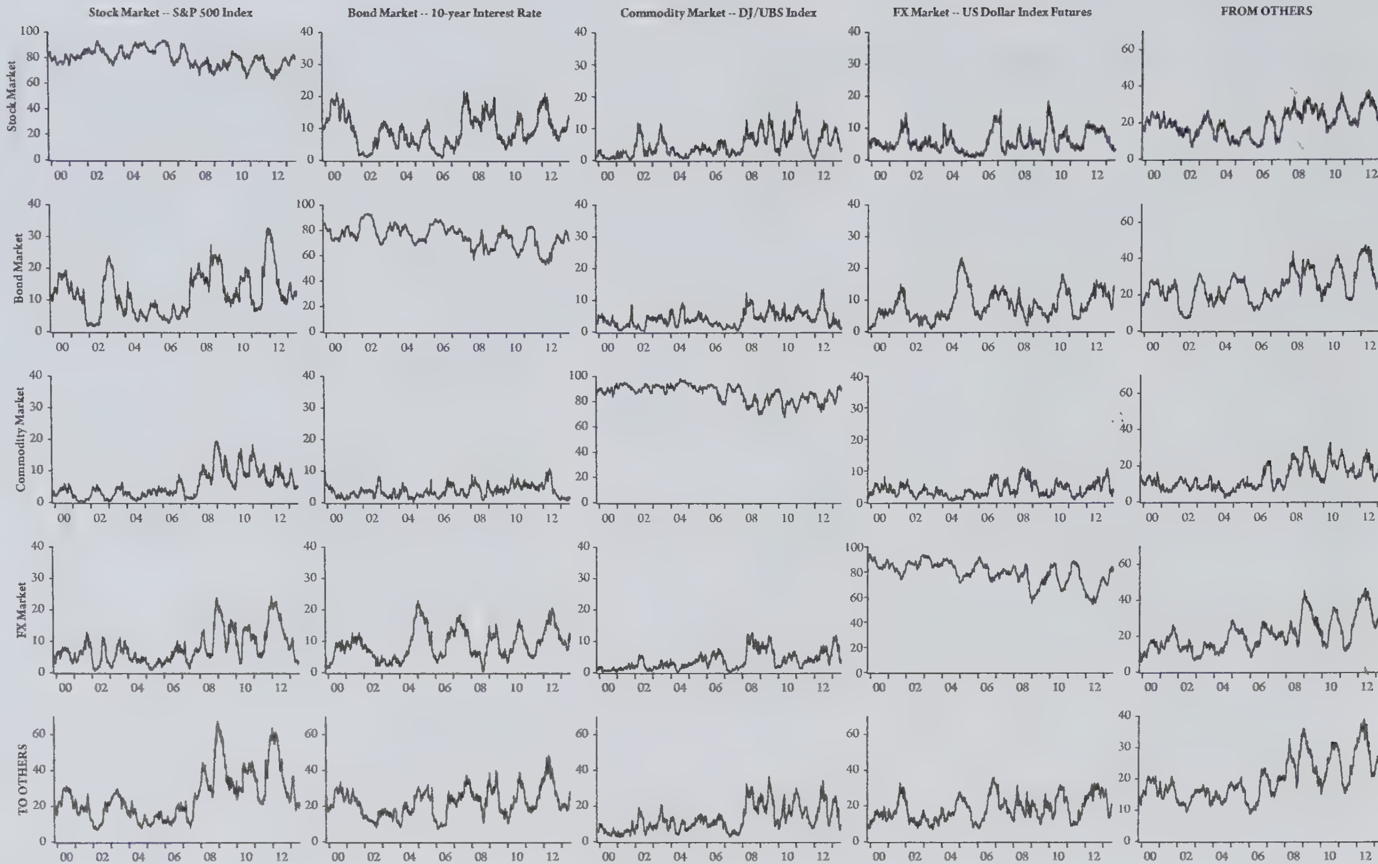


Figure 2.4 Pairwise directional volatility connectedness, four U.S. asset classes (200-day window).

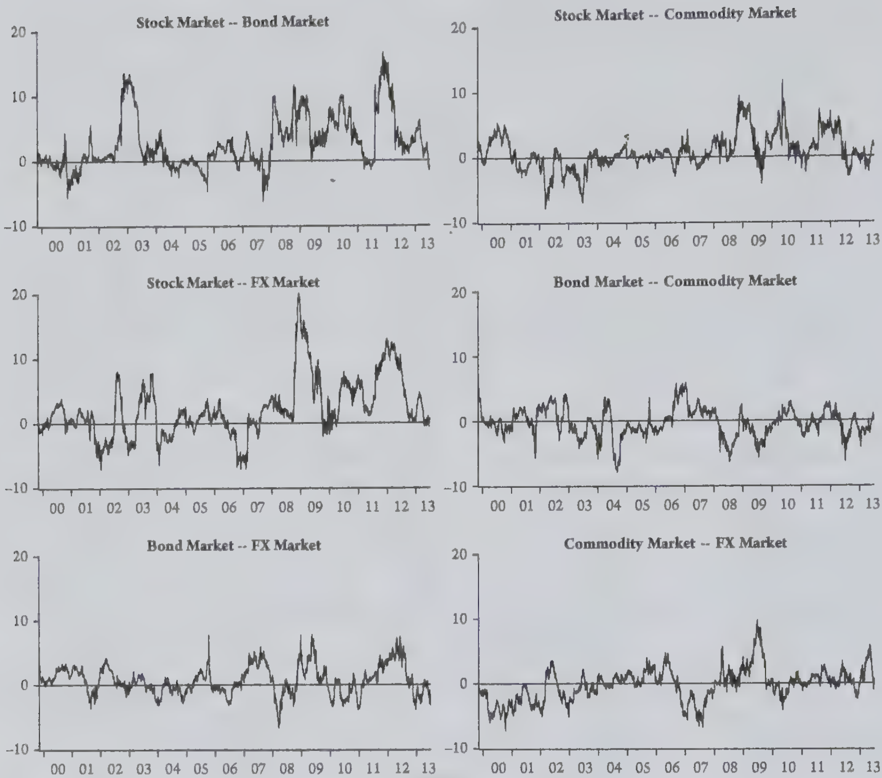


Figure 2.5 Net pairwise directional volatility connectedness, four U.S. asset classes (200-day window).

The second episode of high stock market net connectedness spanned from the second half of 2002 to the third quarter of 2003. Technology stocks continued to be under pressure until October 2002 as the Nasdaq Composite Index hit its lowest level since 1997. In addition, the bankruptcy of WorldCom/MCI led to substantial volatility in the U.S. stock markets. During this episode, the total connectedness index increased from 7.5% in June 2002 to 15% in June 2003. The net volatility connectedness of the stock market increased to 20% during the same period (Figure 2.3). The net pairwise connectedness from the stock market to the bond market increased substantially to reach 15%: It was the strongest pairwise connectedness the stock market had during the bankruptcy of WorldCom/MCI, followed by 8% net pairwise connectedness with the FX market (Figure 2.5). After fluctuating around −5% from September 2001 to June 2002, the net pairwise connectedness of the stock market with the FX market jumped to 8% in June 2002 before declining back to −5% for the rest of 2002 and early 2003. The stock market's net pairwise connectedness with the commodity market, however, was negative throughout 2002 and for most of 2003, fluctuating between 0% and −10%. The negative value for the stock market's net pairwise connectedness with the commodity market indicated that the increased volatility in the commodity market due to the impending war in Iraq at the time generated connectedness toward the stock market.

While the first two episodes of the high stock market "net" connectedness coincided with important political and financial developments, the third took place during the worst crisis to hit the global financial markets. In the third episode, the "to" connectedness first jumped to 20% during the liquidity crisis of July–August 2007, then to 40% in early 2008, and all the way to 65% following the collapse of Lehman Brothers (Figure 2.3). While the "net" connectedness of the stock market did not increase much during the liquidity crisis of July–August 2007, it jumped to 15% and 33% during the following two bouts of hefty volatility connectedness across financial markets, respectively (Figure 2.3). During the January–March 2008 episode, the pairwise connectedness of the stock market with the bond market increased to 10%, but it went down immediately after J. P. Morgan's takeover of Bear Stearns in late March. Following the Lehman Brothers bankruptcy, the pairwise connectedness of the stock market with the commodity market increased to 10%, while its pairwise connectedness with the FX market jumped all the way to 20%. During this episode, its connectedness with the bond market also increased to 10% level (see Figure 2.5).

Even though it came down from 65%, the "to" connectedness of the stock market stayed as high as 30% when it was believed that the worst was over in mid-2009. The net connectedness of the stock market increased again in the first half of 2010, as EU leaders waited more than 6 months to come up with a response to the Greek debt crisis. From late 2009 to May 2010, EU leaders had done nothing to address the sustainability of the Greek government's debt. As a result, during this period, volatility in the European financial markets increased significantly. The "to" and "net" connectedness of the stock market increased to 44% and 25%, respectively (see Figure 2.3). Its net pairwise connectedness with the bond market jumped to 10%, and the net connectedness to the commodity and FX markets jumped to around 12% and 8%, respectively. During the late 2011 episode of the eurozone debt crisis, the "to" and "net" connectedness of the stock market gradually went up to 33% and 64%, respectively (see Figure 2.3). Most of the increase in the "net" connectedness of the stock market was accounted for by its connectedness to the bond market, which increased to 17%, followed by the FX market, which increased to 13% (see Figure 2.4). Finally, during the "fiscal cliff" showdown in late 2012, the "to" and "net" connectedness of the stock market increased slightly to 36% and 11%.

The net volatility connectedness of the other three financial markets fluctuated throughout the sample period as well. However, their fluctuations mostly took place in negative territory, indicating that they were on the receiving end of the volatility shocks that stem from the stock market. The net connectedness of the bond market never reached 20%. It declined to values lower than –10% on several occasions, mostly during the global financial crisis and the European debt crisis. The net connectedness of the commodity market, on the other hand, reached the 10% level on several occasions, namely, in 2002, 2003, 2004, 2009, and 2012. The net connectedness of the FX market reached the 10% level after the terrorist attacks in 2001, as well as in 2006 after Fed surprised the markets by increasing the federal funds rate to 5.0% at its meeting on May 10, 2006. Following the bankruptcy of Lehman Brothers, the net connectedness of the FX market declined to around –30%, indicating that the FX market was a net recipient of the volatility shocks transmitted by the stock market during the worst financial crisis in recent history. Finally, starting around –5% in the summer of 2011, the net connectedness of the FX market gradually declined to –20% in mid-2012. Its net connectedness with all three markets move into negative territory during this period.

2.4 CONCLUDING REMARKS

In this chapter, we have provided both gross and net *directional* connectedness measures that are independent of the ordering used for volatility forecast error variance decompositions. When applied to U.S. financial markets, our measures shed new light on the nature of the cross-market transmission of volatility, pinpointing the importance of volatility connectedness from the stock market to other markets. Throughout the 14 years covered in the analysis, there were many episodes of volatility connectedness taking place from the U.S. stock market to other U.S. financial markets. There were substantial differences across the cases in terms of the source of volatility. Even when the events that triggered higher volatility started in the EU, the directional volatility connectedness was, for the most part, from the stock market to other markets. This result shows that in the case of the United States the stock market plays a pivotal role. When the shock takes place abroad, in the United States it first leads to an increase in volatility in the stock market, which then spreads the shock to other markets.

We will later expand our analysis to include more countries and analyze whether the stock market plays such a pivotal role when financial market volatility in other industrial countries is taken into account.

2.A APPENDIX: STANDARD ERRORS AND ROBUSTNESS

In this appendix, we present two sets of important information for the reliability of the results presented in the chapter. Since they are not central to the analysis, we decided to present these results in the appendix. In order to be able to focus more on substantive results, in the rest of the book we delegate the discussion of the sensitivity analysis results to the appendix as well.

Table 2.A.1 Volatility Connectedness Table with Standard Errors, Four U.S. Asset Classes

	Stocks	*Bonds*	*Commodities*	*FX*	*FROM*
Stocks	83.8**	11.1**	0.7*	4.4**	16.2**
	(1.39)	(1.04)	(0.29)	(0.78)	(1.39)
Bonds	15.3**	75.6**	1.1**	8.0**	24.4**
	(1.19)	(1.49)	(0.32)	(0.86)	(1.49)
Commodities	0.9*	0.9**	95.0**	3.2**	5.0**
	(0.36)	(0.32)	(0.88)	(0.58)	(0.88)
FX	7.2**	7.9**	3.1**	81.8**	18.2**
	(0.95)	(0.82)	(0.57)	(1.42)	(1.42)
TO	23.4**	19.9**	4.9**	15.6**	
	(1.81)	(1.54)	(0.87)	(1.52)	
NET	7.2**	–4.5**	–0.1	–2.6	**15.9****
	(1.67)	(1.38)	(0.90)	(1.41)	(0.94)

Notes: The sample is January 25, 1999 through June 28, 2013. Bootstrapped standard errors are presented in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively.

First, Table 2.A.1 presents the full-sample total volatility connectedness table along with the standard errors for each pairwise and total directional connectedness measures obtained through the nonparametric bootstrap method with 5000 resamplings. All pairwise connectedness measures are statistically different from zero at the 1% or 5% level. All "from" and "to" connectedness measures are also strongly significant. Only the "net" total connectedness measures of the commodity and exchange rate volatilities are not statistically different from zero.

Figure 2.A.1 presents the sensitivity analysis of the dynamic total connectedness index with respect to the choice of the order of the VAR model (ranging from 1 through 6) and the forecast horizon (6, 12, or 18 days) to calculate the variance decompositions of the estimated VAR model. For each alternative forecast horizon considered, the lower and the upper bounds of the gray-shaded band correspond to the total connectedness index with VAR order of 1 day and 6 days, respectively. The solid black line in the middle is the total connectedness index from our benchmark VAR model of order 3.

The total volatility connectedness plot is robust to the choice of the forecast horizon and/or the order of the VAR model. As we increase the forecast horizon, the gray-shaded band widens slightly, yet the total volatility connectedness increases or decreases in tandem in all three plots and for all VAR model orders considered.

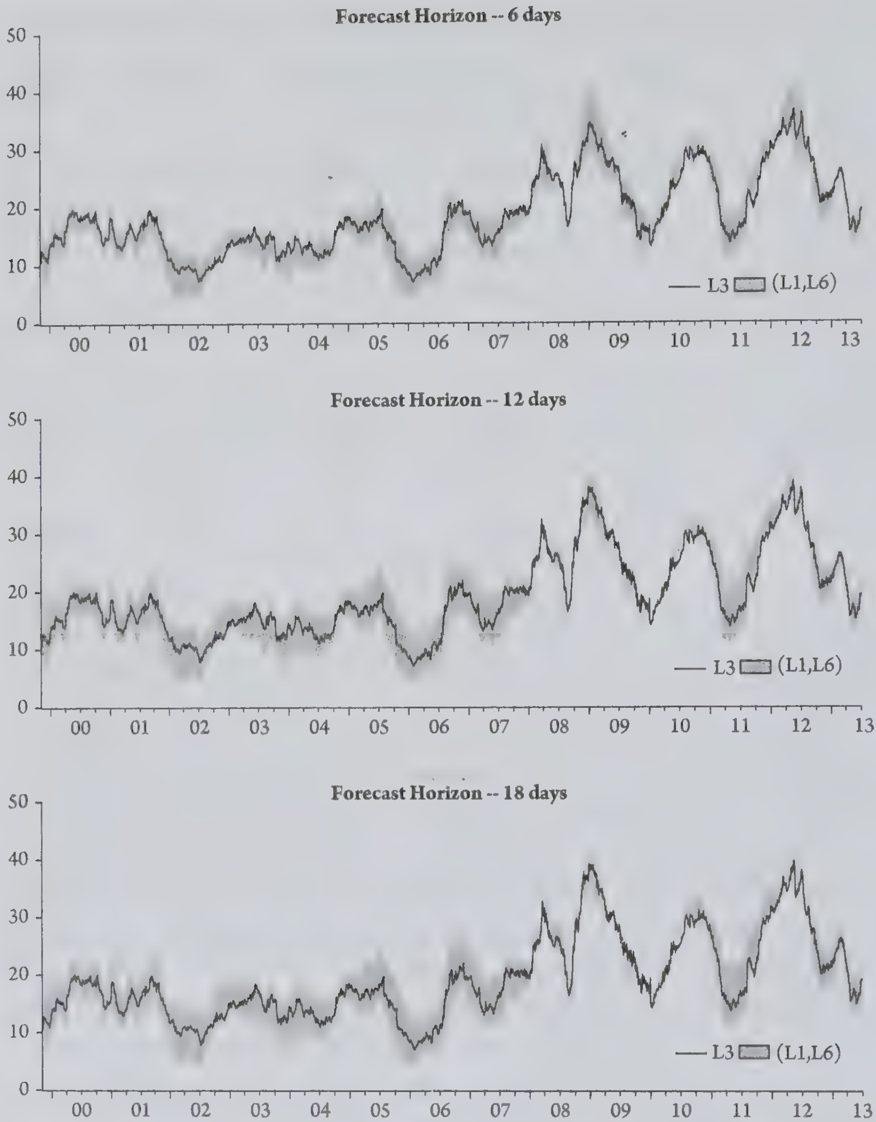


Figure 2.A.1 Robustness to forecast horizon and lag choice, total volatility connectedness across U.S. asset classes.

The lower and upper bands of the shaded area correspond to the total connectedness obtained from a VAR model of stock returns with one lag (L1) and six lags (L6), respectively. The solid black line is the total connectedness obtained from a VAR model with three lags (L3).

3

MAJOR U.S. FINANCIAL INSTITUTIONS

None of us anticipated the magnitude of the ripple effects.
[Merrill Lynch President Gregory Fleming
on the U.S. financial crisis,
as reported in Lowenstein (2010)]

In the first two sections of the book we have introduced tools for connectedness measurement and related them to tools for describing the structure of weighted directed networks. In this chapter we use those tools to monitor and characterize the evolution of connectedness among major U.S. financial institutions before, during and after the 2007–2009 financial crisis. Understanding such financial connectedness is of interest in terms of understanding how the shocks spread across bank stocks during the financial crises.

In the rest of the chapter we proceed in four steps. First, in Section 3.1 we describe the data that we use to measure financial institution connectedness. Next, in Section 3.2 we perform a full-sample (static) analysis, in which we effectively characterize average, or unconditional, connectedness. This not only is of intrinsic interest, but also sets the stage for Section 3.3, where we perform a rolling-sample (dynamic) analysis of conditional connectedness. Our ultimate interest lies there; we monitor high-frequency (daily) connectedness as conditions evolve, sometimes gradually and sometimes abruptly. Finally, in Section 3.4 we "zoom in" on financial institution connectedness during the global financial crisis of 2007–2009.

3.1 VOLATILITY OF BANK STOCK RETURNS

Financial institutions are connected directly through counterparty linkages associated with positions in various assets, through contractual obligations associated with services provided to clients and other institutions, and through deals recorded in their balance sheets. High-frequency analysis of financial institution connectedness therefore might seem to require high-frequency balance sheet and related information, which is generally unavailable.

Fortunately, however, we have available stock market returns and return volatilities, which reflect forward-looking assessments of many thousands of smart, strategic and often privately informed agents as regards precisely the relevant sorts of connections. We use that data to measure connectedness and its evolution. It is important to note that we remain agnostic as to how connectedness arises; rather, we take it as given and seek to measure it correctly for a wide range of possible underlying causal structures.[1]

Volatilities are latent and hence must be estimated. As we have already discussed in Chapter 2, our analysis of volatility connectedness relies on the use of range estimates of daily asset return volatility. However, this chapter differs from the rest of the book. The availability of five-minute stock return data for major U.S. financial institutions allowed us to use daily realized volatilities in this chapter.[2] For a given firm on a given day, we construct daily realized return volatility using high-frequency intra-day data from the Trade and Quote (TAQ) database. In particular, we calculate daily realized volatility as the sum of squared log price changes over the 78 five-minute intervals during trading hours, from 09:00–12:00 and 13:00–16:30.

As we discussed in Section 1.3, we treat realized volatility as the object of direct interest.This is appropriate because for the large, heavily traded firms that we examine, five-minute sampling is frequent enough largely to eliminate measurement error, yet infrequent enough such that microstructure noise (e.g., due to bid–ask bounce) is not a concern. In addition, and importantly, realized volatility actually *is* an object of direct interest, traded in the volatility swap markets, in contrast to underlying quadratic variation or any other object that realized volatility may or may not be construed as estimating.

Volatilities tend to be strongly serially correlated—much more so than returns, particularly when observed at relatively high frequency. We will capture that serial

[1] Obviously there are trade-offs, but we prefer an approach that potentially achieves much under minimal assumptions, in contrast to a more deeply structural approach that in principle could achieve even more, but only under heroic assumptions, and that may not be robust to violations of those assumptions.

[2] Realized volatility has received significant attention in recent years. For surveys see Andersen et al. (2006a, 2010, 2013).

correlation using vector-autoregressive approximating models, as described earlier. Volatilities also tend to be distributed asymmetrically, with a right skew, and approximate normality is often obtained by taking natural logarithms. Hence we work throughout with (natural) log volatilities.

3.2 STATIC (FULL-SAMPLE, UNCONDITIONAL) ANALYSIS

Here we study stock return volatilities for 13 major U.S. financial institutions that survived the crisis of 2007–2009. In Table 3.1 we list the firms, tickers, market capitalization before and after the crisis, and critical episodes/dates during the crisis. Our sample includes seven commercial banks, two investment banks, one credit card company, two mortgage finance companies, and one insurance company. Stocks of all firms except Fannie Mae and Freddie Mac were included in the S&P 500 index prior to the sub-prime crisis of 2007.

Our sample begins in May 1999 and ends in April 2010. Starting in 1999 allows us to include among our firms Goldman Sachs, Morgan Stanley, and U.S. Bancorp,

Table 3.1 U.S. Financial Institution Detail

Institution	*Ticker*	*Business*	*Market Cap.*	
			12/29/06	*12/31/09*
J. P. Morgan Chase	JPM	C-Bank	169	171
Wells Fargo	WFC	C-Bank	121	137
Bank of America	BAC	C-Bank	241	131
Citigroup	C	C-Bank	274	76
US Bancorp	USB	C-Bank	64	43
Bank of NY Mellon	BK	C-Bank	30	34
PNC Bank	PNC	C-Bank	22	24
American Express	AXP	Credit Cards	74	49
Goldman Sachs	GS	I-Bank	86	86
Morgan Stanley	MS	I-Bank	85	40
Fannie Mae	FNM	Mortgages	59	1.3
Freddie Mac	FRE	Mortgages	47	0.9
AIG	AIG	Insurance	187	4

Notes: C-Bank denotes a commercial bank, and I-Bank denotes an investment bank. Market capitalizations are in billions of U.S. dollars. Fannie Mae and Freddie Mac were placed in government conservatorship on September 7, 2008, and AIG began government ownership on September 17, 2008.

all of which went public in the late 1990s. Our sample also spans several important financial market episodes in addition to the crisis of 2007–2009.[3] These include the dot-com bubble collapse of 2000, the Enron scandal of October 2001, and the WorldCom/MCI scandal and bankruptcy of July 2002. Hence we can not only assess connectedness of our firms during the crisis of 2007–2009, but also compare and contrast connectedness during other episodes.

Perhaps our decision to include AIG deserves some discussion. We include AIG because it was a major supplier of "financial insurance" in the 2000s, selling credit default swaps (CDSs) through its AIG Financial Products arm in London. Although CDSs provided lucrative business for AIG early on, contributing close to 17% of revenue in 2005, they singlehandedly brought down AIG as the financial crisis of 2007–2009 spread across financial markets.

In line with our discussion in Section 1.2, we choose the vector autoregression (VAR) as our approximating model. Furthermore, we choose the VAR to be of order 3. We experimented with longer lags with no significant change in our results. The forecast horizon (H) for the underlying variance decomposition is 12 days. In the dynamic rolling-sample analysis of Section 3.3 we experiment with 6 and 18 days forecast horizons.

The full-sample static volatility connectedness table appears as Table 3.2. Along with the connectedness measures, we have obtained corresponding nonparametric bootstrapped standard errors. However, in order not to clutter Table 3.2 with detailed information, we present the standard errors in Table 3.A.1 in Section 3.A. All pairwise and "from" and "to" connectedness measures are statistically different from zero at the 1% level. Some banks' "net" connectedness measures are not statistically different from zero, indicating that they are neither the "net-receivers" nor the "net-transmitters" of volatility shocks.

Let us begin with the pairwise directional connectedness measures, $\tilde{C}^H_{i\leftarrow j}$, which are the off-diagonal elements of the 13×13 matrix. A quick inspection of Table 3.2 shows that the highest pairwise connectedness measure observed is from Freddie Mac to Fannie Mae ($\tilde{C}^H_{FNM\leftarrow FRE} = 22\%$). In return, the pairwise connectedness from Fannie Mae to Freddie Mac ($\tilde{C}^H_{FRE\leftarrow FNM} = 17.6\%$) is ranked second. The two mortgage finance companies have been viewed very much as twins by the markets and it is quite normal that their pairwise connectedness measures are quite high. When we net the two gross measures out, the resulting net pairwise directional connectedness from Freddie Mac to Fannie Mae is 4.4%, that is, $\tilde{C}^H_{FRE,FNM} = 4.4\%$.

The next highest pairwise directional connectedness takes place from Morgan Stanley to Goldman Sachs ($\tilde{C}^H_{GS\leftarrow MS} = 13.3\%$), two top investment banks that were

[3] The 2007–2009 crisis may itself be split into the sub-prime/liquidity crisis of 2007 and the global financial crisis of 2008–2009.

Table 3.2 Volatility Connectedness Table, Major U.S. Financial Institutions (100-Day Window)

	AXP	*BAC*	*BK*	*C*	*GS*	*JPM*	*MS*	*PNC*	*USB*	*WFC*	*AIG*	*FNM*	*FRE*	*FROM*
AXP	20.0	8.5	7.1	10.3	5.8	9.8	8.8	5.1	8.0	7.8	3.2	2.6	3.0	80.0
BAC	8.3	19.1	6.0	10.6	5.8	8.0	7.4	6.1	7.1	9.2	4.2	3.5	4.6	80.9
BK	8.4	8.3	18.8	8.4	6.2	9.3	8.5	5.7	8.4	8.3	4.2	2.4	3.0	81.2
C	9.5	9.6	5.4	20.4	4.9	8.7	7.8	5.2	7.0	8.0	5.4	3.5	4.7	79.6
GS	8.2	8.6	6.8	7.6	22.1	8.8	13.3	4.0	6.0	7.6	2.4	1.9	2.6	77.9
JPM	10.2	8.6	7.1	10.6	6.2	18.8	9.5	5.2	7.8	7.3	3.6	2.5	2.6	81.2
MS	9.2	8.3	7.1	8.9	9.8	9.7	20.5	4.2	5.5	7.1	3.4	2.8	3.6	79.5
PNC	7.7	8.8	7.4	8.5	4.6	7.6	6.6	18.1	7.6	8.8	5.2	4.2	4.9	81.9
USB	9.3	9.9	7.6	9.9	5.7	8.7	6.4	5.4	20.1	8.5	4.3	1.6	2.7	79.9
WFC	8.3	10.2	6.5	9.8	6.2	7.6	7.1	5.9	7.3	18.0	3.8	3.8	5.3	82.0
AIG	5.3	7.3	4.9	8.8	2.6	5.2	4.9	6.2	6.0	5.6	27.5	6.6	9.0	72.5
FNM	4.2	5.4	2.5	6.0	2.3	3.5	3.8	5.5	1.9	6.8	6.5	29.6	22.0	70.4
FRE	4.3	6.3	2.9	6.5	2.6	3.3	4.1	5.2	2.9	7.3	7.4	17.6	29.6	70.4
TO	92.9	99.7	71.3	106.1	62.7	90.2	88.2	63.7	75.5	92.2	53.8	53.1	68.1	
NET	13.0	18.8	−9.9	26.5	−15.2	8.9	8.7	−18.2	−4.4	10.2	−18.7	−17.4	−2.3	**78.3**

Notes: The sample is May 4, 1999 through April 30, 2010. All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in the appendix in this chapter, in Table 3.A.1.

able to survive the 2007–2009 financial crisis.[4] While the connectedness from Goldman Sachs to Morgan Stanley is also high ($\tilde{C}^H_{MS\leftarrow GS} = 9.8\%$), in net terms the directional connectedness takes place from Morgan Stanley to Goldman Sachs stock ($\tilde{C}^H_{\mathbf{MS,GS}} = 3.5\%$).

The highest values of pairwise directional connectedness measures among the commercial bank stocks are observed to take place from Citigroup, on the one hand, and Bank of America and J.P. Morgan, on the other ($\tilde{C}^H_{BAC\leftarrow C} = \tilde{C}^H_{JPM\leftarrow C} = 10.6\%$). A high value of pairwise connectedness from Citigroup to either of Bank of America and/or J.P. Morgan shows that being the worst hit institution among the top five commercial banks, Citigroup's stock spread its troubles to the stocks of other top commercial banks.

As we have seen above, Fannie Mae and Freddie Mac are tightly connected to each other. Their pairwise connectedness with AIG also indicated that they are well connected with AIG as well. Pairwise directional connectedness of the stocks of these three institutions with the stocks of each of the remaining financial institutions tend to be much lower than connectedness of other bank stocks in our sample. We need to remind ourselves that these three institutions had lots of difficulties during the 2007–2009 financial crisis and could have gone bankrupt had the U.S. government not intervened in financial markets in September 2008.

The row sum of the pairwise connectedness measures results in the total directional connectedness from others to each of the 13 stocks. In other words, the "FROM" column measures the share of volatility shocks received from other financial firm stocks in the total variance of the forecast error for each stock. By definition, it is equal to 100% minus the own share of the total forecast error variance. As the own effects (diagonal elements of the matrix) range between 18% and 30%, the total directional connectedness in the "FROM" column range between 70% and 82%.

Similarly, the column sum of all pairwise connectedness measures results in the corresponding stock's total directional connectedness to others. As each stock's contribution to others' forecast error variances is not constrained to add up to 100%, entries in the "TO" row can exceed 100%. While the financial stocks are largely similar in terms of receiving volatility shocks from others, they are highly differentiated as transmitters of volatility shocks to others. The stark difference between the distributions of the two connectedness measures is clearly observed in their respective empirical survivor functions presented in Figure 3.1. Compared to the very steep survivor function defined over a narrow range for the connectedness from others, the survivor function for the connectedness to others is quite flat and defined over a wider

[4] As other three investment banks ceased to exist in 2008, they are not included in the full sample connectedness table.

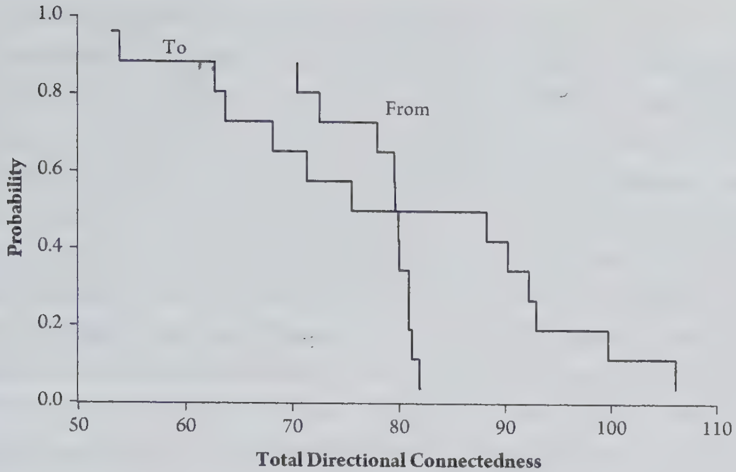


Figure 3.1 Empirical survivor functions for "to" and "from" volatility connectedness, major U.S. financial institutions.

range. Starting at a minimum of 70% for Fannie and Freddie and increasing only up to a maximum of 82% for Wells Fargo and PNC Bank, the total directional connectedness from others is distributed rather tightly. The total directional connectedness to others, on the other hand, varies from a low of 53% for Fannie Mae, to all the way up to 106% for the Citigroup: A range of 53 points for the connectedness to others compared to a range of just 12 points for the connectedness from others.

The largest commercial banks (as of 2010) were the ones that have the highest values of connectedness (all exceeding 90%) to others. Being the most vulnerable among them, Citibank generated a total directional connectedness measure of 106% to others. Besides the top four commercial banks, American Express Bank also generated significant (93%) volatility connectedness to others.

The difference between the total directional connectedness to others and the total directional connectedness from others gives the net total directional connectedness to others($\tilde{C}_i^H = \tilde{C}_{\bullet\leftarrow i}^H - \tilde{C}_{i\leftarrow\bullet}^H$). In terms of the net total directional connectedness, Citigroup (26.5%) leads the way, followed by Bank of America (18.8%), American Express Bank (13%), Wells Fargo (10.2%), and JP Morgan (8.9%). AIG (–19%), PNC Bank (–18%), Fannie Mae (–17%), Goldman Sachs (–15%), and Bank of New York Mellon (–10%) are the financial institutions with negative values of net total directional connectedness to others.

Finally, with a value of 78.3% the measure of total connectedness among the 13 financial stocks is higher than the total connectedness measures we obtained in other settings, such as the connectedness among different asset classes, or among international stock markets. Given the large number of stocks included in the sample, there is a high degree of connectedness for the full sample. As we will see below, there is always a high degree of connectedness even during tranquil times. There is another reason why the total connectedness for a set of financial stocks to be higher than for a set of major national stock markets around the world or for a set of asset classes in the United States. As the institutions included in our analysis are all operating in the finance industry, both industry-wide and macroeconomic shocks affect each one of these stocks one way or the other. As some of these institutions and their stocks are more vulnerable to external and/or industry-wide shocks than others, they are likely to be transmitting these shocks to other financial stocks, generating a higher degree of connectedness to others. Obviously, to the extent that they have important implications for the rest of the industry, idiosyncratic volatility shocks are also transmitted to other stocks. For that reason, compared to a similar number of stocks from different industries, the connectedness for a group of stocks in the finance industry is likely to be higher. It is also likely to be higher compared to the connectedness for a group of global markets, as these markets are not subject to common shocks as frequently as the stocks from the finance industry.[5]

3.3 DYNAMIC (ROLLING-SAMPLE, CONDITIONAL) ANALYSIS

The just-completed analysis of full-sample connectedness provides a good characterization of "average" or "unconditional" aspects of each of the connectedness measures, yet by construction it is silent as to the connectedness *dynamics*. In this subsection we provide a dynamic analysis by using rolling estimation windows. We include the same 13 financial institutions that we included in our earlier full-sample analysis.[6] We start our dynamic analysis with total connectedness, and then we move to various levels of disaggregation (directional and pairwise). We also provide a brief assessment of the robustness of our results to choices of tuning parameters and alternative identification methods.

3.3.1 Total Connectedness

In Figure 3.2 we plot total volatility connectedness over 100-day rolling-sample windows. From a bird's-eye perspective, the total connectedness plot in Figure 3.2 has some revealing patterns. It has two big cycles: One starts in late 2000 and ends in

[5] We have in mind a comparison with the total connectedness indexes reported in Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012).

[6] In the next subsection we specifically focus on the 2007–2009 financial crisis and include the remaining four institutions (Bear Stearns, Lehman Brothers, Merrill Lynch, and Wachovia), all of which ceased trading during the crisis.

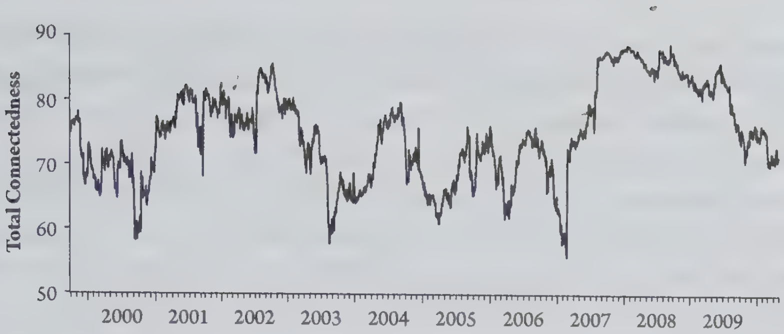


Figure 3.2 Dynamic total volatility connectedness, major U.S. financial institutions (100-day rolling window).

mid-2003, whereas the second coincides with the development of the global financial crisis from early 2007 all the way to the end of 2009. The first cycle coincides with the burst of the dot-com bubble, followed by the downward spiral in Nasdaq and other stock exchanges and the 2001 recession. Even if the recession was over in early 2002, the MCI WorldCom scandal of mid-2002 kept the volatility of the financial stocks and their connectedness high for another year. The second cycle started at the end of February 2007. With the first signs of the sub-prime crisis, the total volatility connectedness index jumped up from a low of around 56% in February 2007 to reach all the way close to 90% in August 2007 and stayed above 80% until mid-2009.

In between the two big cycles of the total connectedness lie three smaller, but not necessarily negligible, cycles. We will discuss each of these cycles along with the events that possibly led to them. Before doing so, let us point to another property of the total connectedness plot. From 1999 to 2007, whenever the total connectedness increased to reach a higher level, reflecting higher volatility of some or all financial stock returns, it always came back down to the 55–70% range as the sample windows are rolled to leave that episode behind. Following the 2007–2009 financial crisis, the total connectedness index stayed well above this range as of the end of April 2010, even though the financial crisis ended almost a year ago.

Earlier on in our sample, developments in the tech-heavy Nasdaq stock exchange influenced the behavior of the total volatility connectedness among the financial stocks. In the late 1990s, U.S. stock markets experienced rapid price increases fueled in greater part by speculative demand for the internet stocks (also called dot-com stocks). Nasdaq composite stock index increased more than fivefold, from around 1000 in January 1996 to more than 5000 in March 2000. Starting in March 2000, the dot-com bubble finally started to burst. After closing at a historical high of 5048 on 10 March 2000, the Nasdaq composite index dropped all the way down to 3000 in two months. This substantial drop in the Nasdaq composite index had its impact on all U.S. stocks. As such, it also had an impact on the total volatility connectedness of financial stocks. In March 2000, the volatility connectedness index increased slightly (approximately 7 percentage points). As the downward move of the Nasdaq composite index subsided temporarily and stabilized around 4000, the total connectedness measure declined in August 2000.

Despite short spells of recovery, troubles of the internet stocks continued for some time. As a result, the rapid decline in the Nasdaq composite index set in again in late September. Nasdaq index that was around 4000 in mid-September dropped all the way down to below 2000 by mid-March 2001. As the problems in the tech stocks worsened, they started to spread to all stocks and the economy. Solid signs of an imminent recession appeared in the horizon. The volatility in the bank stocks increased rapidly over this period, and so did the total connectedness. From a low of 60% in early September, the connectedness index increased to 75% by mid-January 2001 and further to above 80% by early May 2001.

The Federal Reserve's intervention, by way of lowering the Fed funds target rate by 2.5 percentage points in the first five months of 2001, helped stem the decline in the Nasdaq and other markets toward the second and third quarters of 2001. Total connectedness declined to 71% by early September 2001. However, 9/11 terrorist attacks worsened the market sentiment again. Even though the markets were closed for a week after the terrorist attacks, the total connectedness among the financial stocks jumped 10 percentage points in the week it was reopened. The total connectedness stayed around 80% as long as the data for 9/11 were included in the rolling-sample windows.

As the volatility of financial stocks stayed high in the first half of 2002, the total connectedness stayed unchanged slightly above 75%. After the Enron scandal of late 2001, another corporate scandal rocked the U.S. financial markets toward the end of June 2002. This time around it was the bankruptcy of MCI WorldCom, which was once the second-largest long distance phone company in the United States.

For years the management of the MCI WorldCom successfully hidden the company's huge losses through accounting tricks. As the losses continued to increase, it became more and more difficult to hide them through accounting tricks. Once the fraud committed by the top management was discovered by internal auditors, top management was fired and on June 26, 2002 the U.S. Securities and Exchange Commission (SEC) launched an investigation into the use of fraudulent accounting methods. As the news about the scandal were revealed, WorldCom's stock price fell drastically and on July 21 the company had to file for bankruptcy, which at the time happened to be the third largest corporate bankruptcy in U.S. history.

Unlike the Enron scandal, MCI WorldCom scandal had serious impact on major bank stocks. All major U.S. banks had credit positions with MCI WorldCom and hence they all suffered losses when the company declared bankruptcy. In addition, 17 commercial banks including Citigroup, J.P. Morgan and other major banks ended up paying a total of $6 billion dollars to investors for underwriting MCI WorldCom bonds.

Following the bankruptcy, the total connectedness among the major financial institutions jumped from 72% to reach 85% in July 2002, the highest level achieved from the beginning of the sample. However, being an isolated source of loss for the banks, the scandal's impact on the financial system as a whole could be contained. As of the end of 2002, total connectedness subsided very quickly to pre-July 2002 levels. By early 2003 the total connectedness declined to below 70%. After a brief increase following the invasion of Iraq in March 2003, the total connectedness declined to 58% in August 2003.

From August 2003 to February 2007, the total connectedness index went through three smaller cycles, during which it moved within the 55–80% range. The first cycle lasted from August 2003 to March 2005; the second from April 2005 to February 2006; and the third from March 2006 to February 2007. All three cycles closely follow the behavior of long-term interest rates. The link between the volatility connectedness and the long-term rates is directly a result of the choices of the investors. Rising long-term interest rates reflect optimism about the future economic performance. As they expect the growth to pick up, investors sell more defensive stocks such as the financial stocks and instead invest in manufacturing, energy, and airlines sector stocks that are likely to benefit most from an economic recovery.

The three cycles mostly coincide with the tightening of monetary policy. From June 2004 to June 2006, in 17 meetings the Federal Open Market Committee (FOMC) increased the Fed funds target rate steadily from 1.0% to 5.25%. However, the long-term interest rates did not respond to the increase in short-term rates; instead they fluctuated during the period. For example, the 10-year treasury note yield increased from its lowest value of 3.77% in 2004 to 5.23% in June 2006. At the time, Fed chairman Alan Greenspan called the failure of long-term rates to follow the short rates as a conundrum and explained it with the increased foreign investments in U.S. government bonds. Irrespective of the factors behind the "Greenspan conundrum," it is clear that the volatility connectedness among the financial stocks was very much affected by the behavior of the long-term interest rates over time.[7]

3.3.2 Total Directional Connectedness

In Figure 3.3 we show time series of total directional connectedness ("to" and "from" degrees) separately for each firm. The total directional connectedness "to" others

[7] We discuss the "Greenspan conundrum" in detail in Chapter 5.

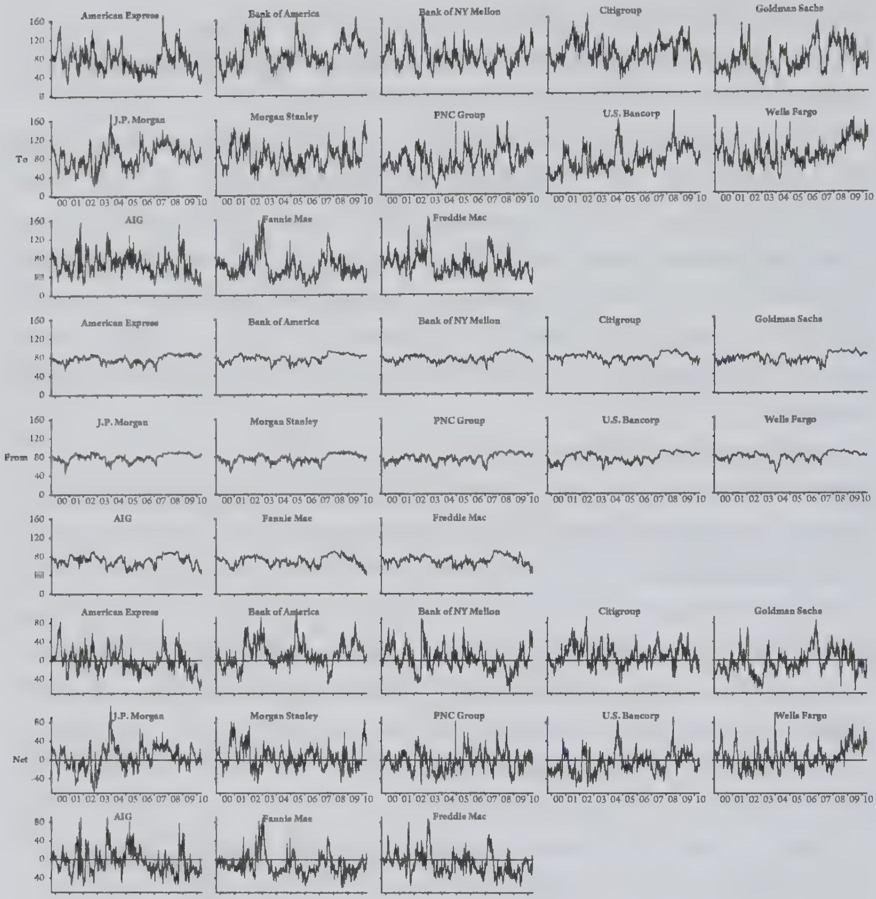


Figure 3.3 Dynamic total directional volatility connectedness, major U.S. financial institutions (100-day rolling window).

plots are presented in the upper panel, the total directional connectedness "from" others plots are in the middle panel, and the "net" total directional connectedness to others plots are in the lower panel.

Looking at Figure 3.3, the first thing that one notes is the substantial difference between the "to" and "from" connectedness plots. The "from" connectedness plots are much smoother compared to the "to" connectedness plots.

The difference between the two directional connectedness measures is not hard to explain. When there is a shock to the return volatility of an individual stock or a couple of stocks, this volatility shocks are expected to be transmitted to other stocks. Since individual institutions' stocks are subject to idiosyncratic shocks some of these shocks are very small and negligible, while others can be quite large. Furthermore, irrespective of the size of the shock, if it is the stock of a larger institution that received the volatility shock, we can expect this volatility shock to have even a larger spillover effect on stocks of other institutions. As the size of the shocks vary as well as the size of the institutions in our sample, the directional connectedness "to" others varies substantially across stocks over the rolling-sample windows.

We have already emphasized that the institutions in our sample are the largest ones in the U.S. financial industry. As a result, none of the stocks in our sample of 13 institutions would be insulated from volatility shocks to stocks of other institutions. In other words, they are expected to be interconnected. As a result, each one will receive, in one form or the other, the volatility shocks transmitted by other institutions. The volatility shocks transmitted "to" others by each individual stock may be large; but when they are distributed among 12 other stocks, the size of the volatility shock received by each stock will be much smaller. That is why there is much less variation in the directional connectedness "from others" compared to the directional connectedness "to others" in Figure 3.3.

The difference between the directional connectedness "to" and "from" others is equal to the "net" directional connectedness to others presented in the lower panel of Figure 3.3. As the connectedness "from" others measure is smooth over the rolling-sample windows, the variation in the "net" connectedness to others plots over the rolling-sample windows resembles the variation in the connectedness "to" others plots.

When we focus on the behavior of the directional connectedness measures over time, we observe that even though "from" others measures for each stock reached the highest levels during the 2007–2009 crisis, we do not observe such a level shift in the "to" other and "net" to others measures during crisis period. This is so, perhaps because idiosyncratic shocks have always hit individual stocks and these shocks have been transmitted to other stocks. During the 2007–2009 crisis, these shocks became significantly larger.

In the initial phase of the sub-prime crisis (February–July 2007), as the mortgage companies start to collapse, the mean "to others" connectedness increased (late February 2007) and the distribution became more fat-tailed. In the spring 2007 (April–May) the distribution widened further, followed by the summer lull and a tighter distribution until the end of July. With the sub-prime crisis turned into an international liquidity crisis at the end of July, the mean degree increased and the distribution became wider, indicating a differentiation taking place among the stocks of major financial institutions. Lehman Brothers was closer to become an outlier in August 2007. Similarly, signs of trouble in Wachovia Bank and Merrill Lynch were already there as of the summer of 2007. In addition to these three banks, American Express Bank had very high (ranked among the top four) directional connectedness "to others." While American Express Bank was not in big trouble, it had a weaker balance sheet than many commercial banks in our sample, because most of its loans were high-risk consumer credit loans financed not by deposits but rather by long-term borrowings.

As the liquidity crisis subsided down, the distribution of the "to others" connectedness became tighter without any decline in the total connectedness. All major banks had to accept their untenable positions and searched ways to raise capital even though that would have diluted the incumbent shareholders' interests. In the first few weeks of 2008 it was JPMorgan Chase stock that had high "to others" volatility connectedness. The problems of Bear Stearns had rather negligible impact on other financial institutions, as can be seen in low values of gross and net pairwise connectedness measures that Bear Stearns had with other stocks. The imminent collapse of Bear Stearns and its implications for the greater market were thwarted by its last minute sale to JPMorgan Chase in a deal engineered within the guises of the Federal Reserve Bank of New York. Even though the slight increase in the median connectedness showed the stress among several banks, especially among the investment banks, the handling of the Bear Stearns within the system calmed the markets for a while.

Then, in the summer of 2008, Wachovia Bank (which is not in our sample of 13 stocks) led the way in terms of directional connectedness among the major bank stocks. It was not a single bank obviously, as there were other banks that were in trouble. As a result, the distribution of directional connectedness "to others" widened substantially in June and July 2008. The wider distribution of the directional connectedness "to others" with fatter tails continued until the collapse of Lehman Brothers in mid-September.

Thus far we have focused on time series of individual node degrees. In closing this section, however, we now show the evolution of the entire "to" and "from" degree *distributions* in Figure 3.4. Although, by definition, the *mean* "to" and "from" directional connectedness measures are both equivalent to the total connectedness measure presented in Figure 3.2, each financial institution has rather different "to" and "from"

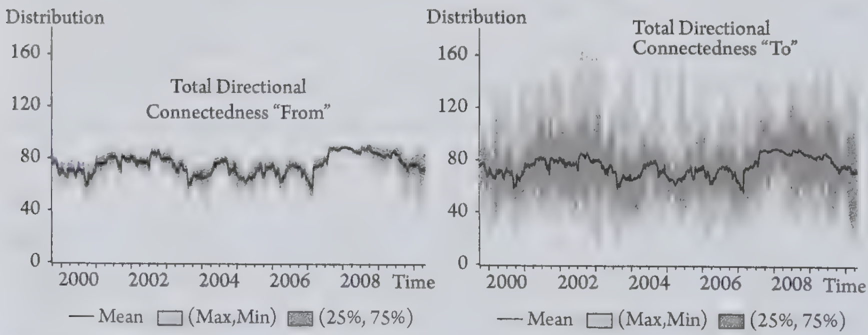


Figure 3.4 Rolling distribution of total directional connectedness, major U.S. financial institutions. We plot the time series of daily min, 25%, mean, 75%, and max of the distributions of the "to" and "from" total directional connectedness. The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days.

directional connectedness. This implies that even though their means are the same, "to" and "from" connectedness are distributed quite distinctively. As emphasized earlier, the variation in the "from" connectedness is much lower than the variation in "to" connectedness. Even the first and second quartile band for the "to" connectedness is wider than the min–max range for the "from" connectedness.

Temporal changes in the dispersion and skew of "to" and "from" connectedness may contain useful information. For example, it appears that "from" connectedness gets not only more dispersed but also more left-skewed during crises and that, simultaneously, "to" connectedness gets more right-skewed. That is, during crisis times relatively more than during non-crisis times, there are a few firms receiving very little and a few firms transmitting very much. One might naturally want to identify firms that are simultaneously "small receipts" and "big transmissions"—those are the distressed firms potentially poised to wreak havoc on the system.

3.3.3 Pairwise Directional Connectedness

In the analysis of the full-sample volatility connectedness in Section 3.2, we discussed the importance of pairwise volatility connectedness measures. In particular, we emphasized the importance of pairwise connectedness as a measure of how volatility shocks are transmitted across financial institution stocks. The relevance of the pairwise connectedness measures carries over to the rolling sample windows. Indeed, the analysis of pairwise connectedness measures are even more crucial in the rolling sample windows case, because it helps us identify how the connectedness across financial institution stocks vary over time. During times of crises, individual stocks are likely to be subject to frequent volatility shocks. How these shocks led to volatility connectedness across pairs of stocks is very crucial for any analysis of crises. Unfortunately, given that there are 13 institutions in our sample from 1999 to 2010, presenting plots of the volatility connectedness (for each of the 156 pairwise directional measures and the 78 net pairwise directional measures) is an almost impossible task to accomplish in the confines of this chapter. Instead, when we are discussing the development of the global financial crisis over time and the volatility connectedness of the most troubled financial institutions during the crisis, we will present and discuss the net pairwise connectedness measures during the most critical days of the crisis.

3.4 THE FINANCIAL CRISIS OF 2007–2009

Having analyzed the dynamics of the various connectedness measures over time, in this section we focus on the global financial crisis, from 2007 through 2009. First, we discuss the stages of the crisis to show how the total volatility connectedness measure behaved as the crisis developed from the sub-prime and liquidity crises of 2007 in the United States into a global financial crisis in October 2008. In the second part of the analysis we focus on the most-troubled financial institutions and their total and pairwise directional volatility connectedness during the critical stages of the crisis.

3.4.1 Total Connectedness at Various Stages of the Crisis

As of the end of 2006, there were already some, albeit weaker, signs of slowdown in the real-estate markets.[8] In late February 2007, the New Century Financial Corporation was reported to have troubles in servicing its debt. It was followed by the bankruptcy of three small mortgage companies. These, in turn, worsened the expectations about the real estate markets, the mortgage-based assets (MBAs), and the stock market. On the last day of February 2007 the total connectedness measure jumped by more than 17 points on a single day. The increase in the total connectedness was not due to a volatility shock to the stock of a single financial institution, but instead all bank stocks were affected by the recent developments in the MBA markets.

The churning in the MBA market continued from February to early June. New Century declared bankruptcy in April. Following the downgrading of different tranches of mortgages by credit rating agencies, in June and July the markets became aware that big financial institutions were not insulated from the debacle in the MBAs. Bear Stearns had to liquidate two of its hedge funds in July, leading to billions of dollars losses for Bears Stearns and the investors in these funds. From early March to late June the total volatility connectedness index climbed gradually from 73% to 80% (see Figure 3.2).

In July 2007, the market for asset backed commercial paper (ABCP) showed signs of a drying-up market, which eventually led to the liquidity crisis of August 2007. From July 25th to August 10, the index climbed 12 percentage points, to reach 88% (see Figure 3.2). Reflecting the developments over the period, the total connectedness index doubled in the first eight months of 2007. After the liquidity crisis of August 2007, it was obvious that the whole financial system will be badly bruised by the collapse of the ABCP market.

After seven months of learning about the problems in MBA markets and the ensuing liquidity crisis, next came the months of reckoning with the consequences as nearly all U.S. banks started to announce huge losses. Many European banks that invested in U.S. MBAs also suffered billions of dollars of losses. In October 2007, some of the worst-effected banks replaced their CEOs and immediately engaged

[8] The Case–Shiller home price index for 20 metropolitan regions was 2% lower in January 2007 compared to its historical high level reached in July 2006.

in search for new capital around the world. Even though it has already reached its historical maximum, volatility connectedness index continued its upward move by a couple of points.

Being the weakest of the five major investment banks, Bear Stearns' problems intensified throughout 2007. With the collapse of its two hedge funds, the company lost billions of dollars. As the MBA markets continued their descent, Bear Stearns financial position became untenable, amid widespread rumors of an eventual bankruptcy, its stock price declined rapidly in mid-March, briefly increasing the tensions and volatility in the markets. In an operation directed by the New York Fed, J.P. Morgan acquired Bear Stearns on 18 March 2007 with financial assistance from the Fed. During the final days of Bear Stearns, the total connectedness for the surviving 13 banks showed an upward movement of only a couple of percentage points. However, as we will analyze below when we include the Bear Stearns' stock in the analysis, we observe an increase in Bear Stearns' net directional connectedness "to others."

There were no major volatility shocks in the stock market after the Bear Stearns' takeover until early June. During this period the total volatility connectedness index declined a couple of percentage points. However, the problems in the real-estate and MBA markets continued to intensify, steadily worsening the balance sheets of the financial institutions that had taken huge positions in these assets.

Throughout the summer of 2008 the tension in the stock market started to build up again. Wachovia's troubles and its stock's resulting high-volatility connectedness were the most important developments throughout the summer. As a result of the volatility originated from Wachovia, the total volatility connectedness index increased from 85% to 88.5% in the first two weeks of July 2008 (see Figure 3.2).

In the meantime, there were failures of regional banks smaller than Wachovia. Independent National Mortgage Corporation (known as IndyMac Bank), which was the largest savings and loan association in the Los Angeles area and the seventh largest mortgage originator in the United States, declared bankruptcy on July 31, 2008. These developments were followed by news about constantly deteriorating asset positions of Fannie Mae and Freddie Mac. While the Treasury wanted to rely more on Fannie Mae and Freddie Mac in dealing with the crisis, over time it became apparent that these Government-Sponsored Enterprises (GSEs) themselves suffered huge losses through their investments in the mortgage and MBA markets. The two GSEs were taken to the explicit government conservatorship in the first week of September.

Then came the most significant event in the unfolding of the crisis. Following the news that Lehman Brothers will announce huge losses in its latest financial statement, market participants started selling Lehman Brother stocks. Despite the overwhelming efforts over the weekend of September 13–14, no viable takeover bid could be produced for Lehman Brothers by the interested institutions. The U.S. government did not want to step in to save the Lehman Brothers with taxpayer money. As soon as the Lehman Brothers declared bankruptcy in the morning of September 15, 2008, pandemonium broke out in financial markets around the world. The same day the weakest of the three remaining investment banks, Merrill Lynch, announced it was being acquired by the Bank of America. The total volatility connectedness index increased further to reach its maximum level of 89.2% (see Figure 3.2).

Two other institutions that had serious trouble after the collapse of Lehman Brothers were the insurance giant AIG and Morgan Stanley, the fourth largest investment bank as of the end of 2006. AIG came under intense pressure following the collapse of Lehman Brothers, due to the Credit Default Swaps (CDS) it issued for the corporate bonds of Lehman Brothers as well as many other corporations. Morgan Stanley stock suffered substantially in the second half of September and October 2008, following the bankruptcy of Lehman Brothers.

The government had to step in when the crisis spread to AIG. The U.S. Secretary of the Treasury, Hank Paulson, was criticized for saving AIG while letting Lehman Brothers go bankrupt. Saving Lehman Brothers would have been much less expensive. However, it was also true that, had the AIG gone under, no one could have figured out the consequences for the United States and the global financial system.

Perhaps saving the AIG from the brink of collapse prevented a financial meltdown, but it was not sufficient to calm the markets. There were other financial institutions that were in trouble. On September 25, the Office of Thrift Supervision (OTS) seized Washington Mutual Bank (WaMu) and placed it on the receivership of the Federal Deposit Insurance Corporation (FDIC). With 328 billion in assets, Washington Mutual Bank was the sixth largest bank in the United States as of the end of 2007. It was the largest financial institution bankruptcy in the U.S. history.

Immediately after WaMu, the attention shifted to Wachovia again, the fourth largest bank in the United States. Wachovia's stock price declined by 81% on September 29. Days away from an eventual bankruptcy, Wachovia top management along with FDIC officials started searching for a suitor for their bank. Citigroup, which was itself in deep trouble, was interested, perhaps to use Wachovia as an excuse for receiving substantial amount of federal loans to keep afloat. However, as the Citigroup was taking its time and pushing the Wachovia board to accept tougher terms, Wells Fargo showed a keen interest in purchasing Wachovia with no government funds involved. Both the board of Wachovia and the FDIC preferred the sale of Wachovia to Wells Fargo. The deal was announced on October 3.

Obviously, it was not only a couple of financial institutions that were in trouble in late September and the first half of October 2008. The global financial markets were all in turmoil as the U.S. Treasury and the Federal Reserve were trying to convince the U.S. Congress about the necessity of direct injection of cash to the U.S. banks in one form or the other. Toward that aim the two institutions prepared the Troubled Asset Relief Program (TARP) that gave the full authority to the Secretary of the Treasury to purchase troubled assets and equities from the banks worth up to $700 billion. By removing the nonperforming assets from the banks' balance sheets, the authorities hoped that the banks will open the credit lines and hence provide liquidity to the system. The TARP bill was initially rejected by the House of Representatives on September 29. As a result, all bank stocks were pounded as the Dow Jones Industrial Average dropped by 778 points on the same day.

Being the weaker one of the last two investment banks left, Morgan Stanley experienced enormous difficulty in the days after the Lehman collapse. The stock was targeted by short-sellers, mostly hedge funds. It lost more than 40% of its value from September 15 to September 18. In order to avoid the fate of Lehman Brothers, the management started to search for interested parties that might invest in the company. As the news that Mitsubishi Bank of Japan was interested in investing in the company got out on September 19, the stock price jumped 21%. On Sunday September 21, the Fed approved the applications of Goldman Sachs and Morgan Stanley to be converted to commercial banks and become eligible for funding from the Federal Reserve using the same collateral as commercial banks.

Morgan Stanley's fortunes turned sour again as the Washington Mutual was taken to the receivership of the FDIC and the TARP was rejected by the House of Representatives. On October 10, the stock closed below $10, recording a 75% decline in one month. That week the revised TARP bill was approved by both chambers of the U.S. Congress. The common stock sale to Mitsubishi Bank was finalized on the weekend of October 11–12. The same weekend the U.S. Treasury announced that the TARP money will be mostly used to inject capital to the already battered financial institutions. Following these announcements, financial stocks including that of the Morgan Stanley started to recover.

The financial stocks came under pressure again in the week of November 16–21. Citigroup's balance sheet continued to worsen, making it a source of real worry for the market participants. Over the weekend of November 22–23, the government officials and Citigroup executives agreed on a plan to effectively bail out the bank. In addition to $25 billion in funds provided through TARP in October, the Treasury provided $20 billion to Citigroup. Furthermore, the government effectively guaranteed potential losses on Citigroup's $335 billion portfolio, in exchange for preferred shares and warrants. As a sign of continued pressure in the markets, in its December 16 meeting the FOMC further lowered the Federal funds rate by 0.75% to 1.0% and allowed it to fluctuate between 0% and 0.25%.

After months of gyrations in the U.S. financial system, the volatility connectedness started to subside down toward the end of the first quarter of 2009. After March 2009, total connectedness measure fluctuated between 80% and 85% for a while. It started to fall only in the summer of 2009. By October 2009 the index was down to the 70%–75% range. However, the news coming from Greece and the EU's inability to handle the Greek debt crisis in an orderly manner led to further volatility in financial industry stocks in the EU and the United States, which prevented the volatility connectedness index to decline any further. As of the end of our sample, the index was fluctuating between 70% and 75%, a range which is above the levels the index attained during tranquil times (see Figure 3.2).

3.4.2 Pairwise Connectedness of Troubled Financial Institutions

So far we have discussed the behavior of the total connectedness and total directional connectedness measures for a group of 13 institutions along with the background of the events that took place in the U.S. financial markets during the financial crisis of 2007–2009. Our analysis did not include four major banks that disappeared during the crisis through bankruptcy or acquisitions. In the remainder of this section, we analyze the total directional and pairwise directional connectedness measures for these four institutions as well as for AIG and Morgan Stanley, two other troubled yet survived institutions. In Table 3.3 we list the information on the four major banks that cease to exist, with information on their stock tickers, market capitalization before the crisis, and critical dates during the crisis.

We present the net total directional connectedness plots for Bear Stearns, Lehman Brothers, Wachovia, Merrill Lynch, AIG, and Morgan Stanley in Figure 3.5 and analyze the dynamics of their net total directional connectedness with the stocks of other

Table 3.3 Detail for Financial Institutions Acquired or Bankrupted During the Crisis of 2007–2009

Institution	*Ticker*	*Business*	*Market Capitalization*		
			(12/29/06)	*Important Events*	
Bear Stearns	BSC	I-Bank	19	Acquired by JPM	3/17/08
Lehman Brothers	LEH	I-Bank	41	Bankruptcy	9/15/08
Merrill Lynch	MER	I-Bank	82	Acquired by BAC	9/15/08
Wachovia Bank	WB	C-Bank	115	Acquired by WFC	10/3/08

Notes: I-Bank denotes an investment bank, and C-Bank denotes a commercial bank. Market capitalizations are in billions of U.S. dollars.

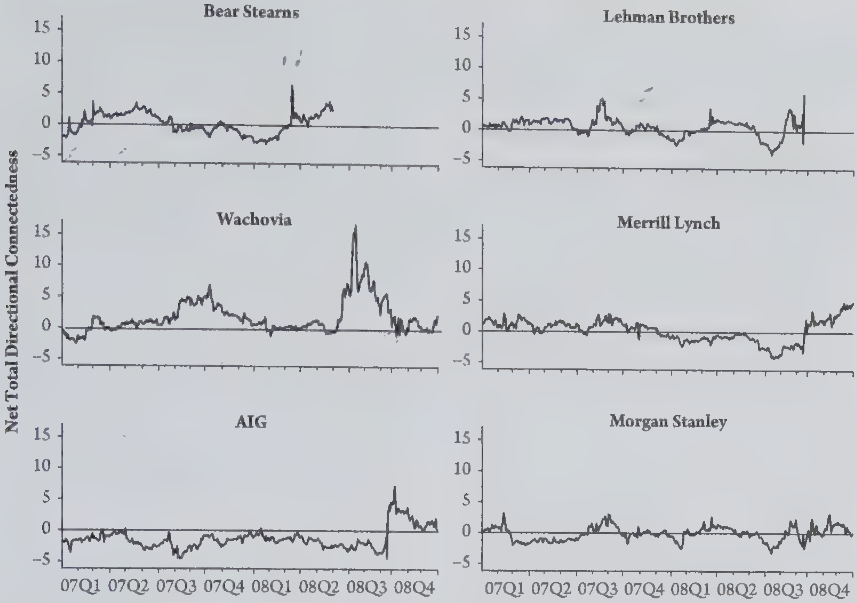


Figure 3.5 Net total directional connectedness of troubled financial firms.

institutions during the financial crisis.[9] Let us spell out the most important observation in Figure 3.5: Even though it was the troubles of the investment banks that were followed the most throughout the crisis, Wachovia Bank is the one that had the highest net total and pairwise volatility connectedness in the climactic months of the second half of 2008.

Coming back to the four troubled investment banks, it was true that they had high net connectedness at several occasions as the global financial crisis unfolded steadily in 2007 and 2008. To start with the most vulnerable of the top 5 investment banks, in the run up to its takeover by J.P. Morgan on March 17, 2008, the net volatility connectedness of the Bear Stearns stock was not sizable. Bear Stearns' net volatility connectedness was high only on Friday, March 14 (close to 6.4%) and Monday, March 17 (4.9%) (see Figure 3.5). As we have already discussed above, Bear Stearns' net volatility connectedness in March through June 2007 was higher. However, in the

[9] It is worth noting that connectedness measurements generally will not, and should not, be robust to choice of reference universe. Hence, given a decision as to the x to be examined, a second important issue is precisely which (and hence how many) x's to use. For example, in this chapter's analysis of individual financial institution equity return volatilities, we intentionally use only the largest firms. In addition, note that our reference universe will change with "births" and "deaths" of financial firms. Births happen, for example, when a firm goes public as with Goldman Sachs in 1999, and deaths happen when firms go bankrupt as with Lehman Brothers in 2008.

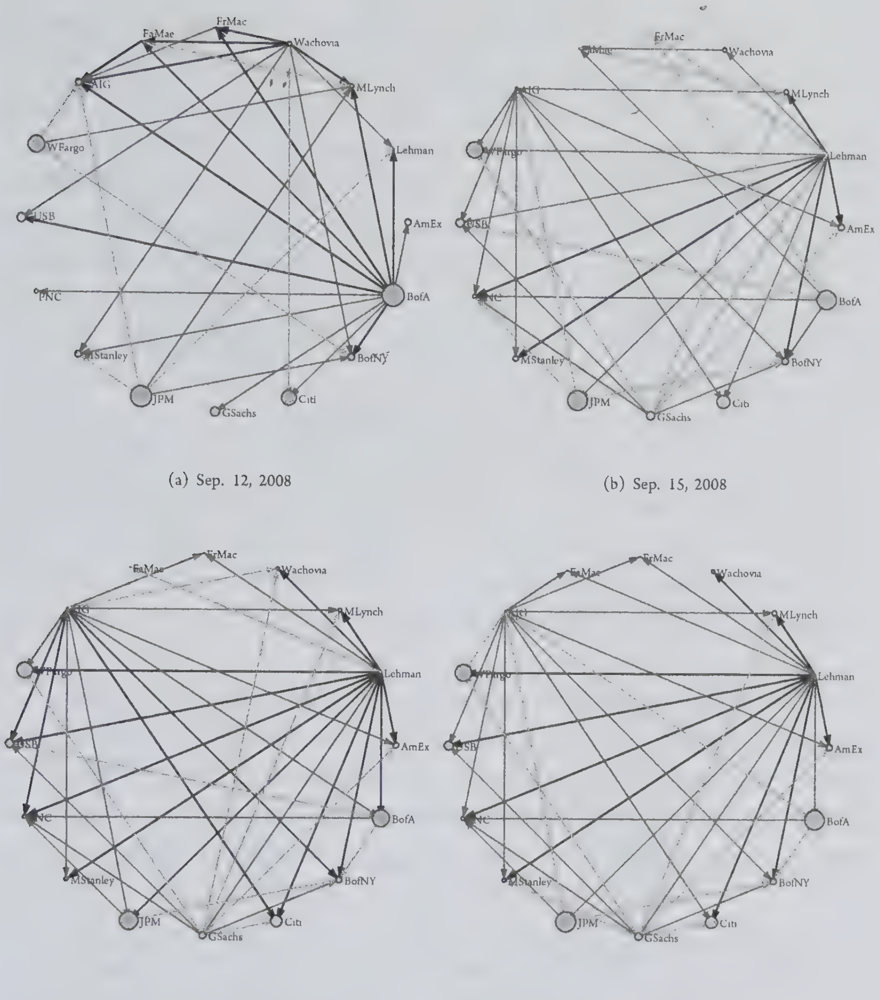
three months prior to its demise, its net total directional connectedness was negative, indicating that it was on the receiving end of the volatility shocks from other stocks.

Viewed as the most vulnerable investment bank after Bear Stearns, Lehman Brother's net directional connectedness during the liquidity crisis of 2007 was close to 5%. It also generated close to 4% net directional connectedness on the day Bear Stearns was taken over by J.P. Morgan (Figure 3.5). Furthermore, its net directional connectedness stayed around 2% for almost three months after the demise of Bear Stearns. As the news about Wachovia's troubles dominated the market from early June till early August and Lehman Brothers stayed as a net receiver of volatility shocks. This status, however, did not last for long. Lehman again became one of the front runners in terms of net directional connectedness (close to 4%) in the first 20 days of August. As the focus shifted to Fannie Mae and Freddie Mac's troubles and their being undertaken to the government conservatorship, the net volatility transmission by Lehman declined in the first week of September.

Figure 3.6 presents the most significant net pairwise volatility connectedness measures of the major U.S. financial institutions included in our analysis during the fateful days (Friday, September 12 through Wednesday, September 17, 2008) that included the bankruptcy of Lehman Brothers.

On Friday, September 12, 2008, just one day before the critical weekend, Lehman Brothers was not at the center stage in terms of volatility connectedness; its net total directional volatility connectedness was less than 1% (see Figure 3.5). Its net pairwise connectedness with none of the other financial stocks was significant enough to make to the top 10 percentile of all the net pairwise volatility connectedness took place between June 1 and December 31 of 2008 (see the stringball plot in Figure 3.6(a)). Only after the announcement of its bankruptcy on the morning of September 15, the Lehman Brothers' stock moved to the center stage in the crisis and generated substantial volatility connectedness. Its net total directional connectedness jumped to 6% on September 15 (Figure 3.5). Its net pairwise connectedness with five financial stocks was in the top one percentile (another five were in the top five percentile and two were in the top 10 percentile) of all the net pairwise volatility connectedness and took place between June 1 and December 31 of 2008 (Figure 3.6(b)). Lehman Brothers' net pairwise directional connectedness increased substantially in the last two trading days of the stock, September 16 and 17 (see Figures 3.6(c) and 3.6(d)).

In order to bring forth the bank stocks that played a more central role in generating volatility connectedness to others during the last few days of Lehman Brothers, in Figure 3.7 we present the same information in Figure 3.6 in an alternative arrangement proposed by Kamada and Kawai (1989). As can be seen in Figure 3.7(a), while Wachovia and the Bank of America were at the center of the "star-shaped" connectedness graph on 12 September 2008, Lehman Brothers did not generate significant net



(a) Sep. 12, 2008

(b) Sep. 15, 2008

(c) Sep. 16, 2008

(d) Sep. 17, 2008

Figure 3.6 Net pairwise directional connectedness during the Lehman bankruptcy.
Notes: We show the most important directional connections among the pairs of 16 bank stocks on each day. Black, gray, and light gray correspond to the first, fifth, and tenth percentiles of all net pairwise directional connections from June 1 to December 31, 2008. Node size indicates stock market capitalization.

volatility connectedness to others that day. On Monday, September 15, however, the graph changed dramatically. Lehman Brothers and AIG moved to the center of the graph; Lehman having more significant connectedness to others than AIG. The net pairwise volatility connectedness of Lehman Brothers and AIG intensified even more on September 16 and 17. In both days, Goldman Sachs also had quite significant net pairwise connectedness to others. As Kamada and Kawai (1989) arrangement-based graphs and the string-ball graphs are quite complementary in terms of their emphases, in the rest of this section we will use two sets of graphs interchangeably.

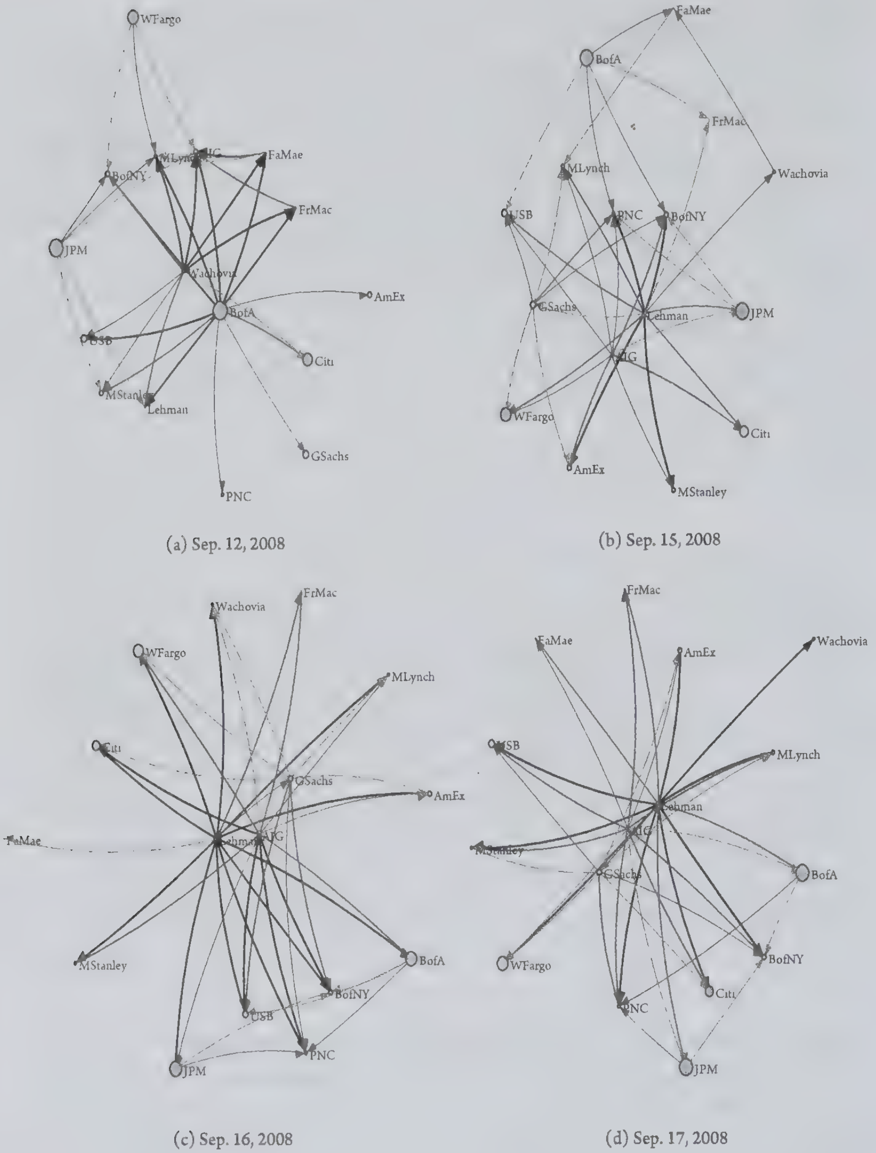


Figure 3.7 Net pairwise directional connectedness during the Lehman bankruptcy with Kamada and Kawai (1989) node arrangement.
See Figure 3.6 for details.

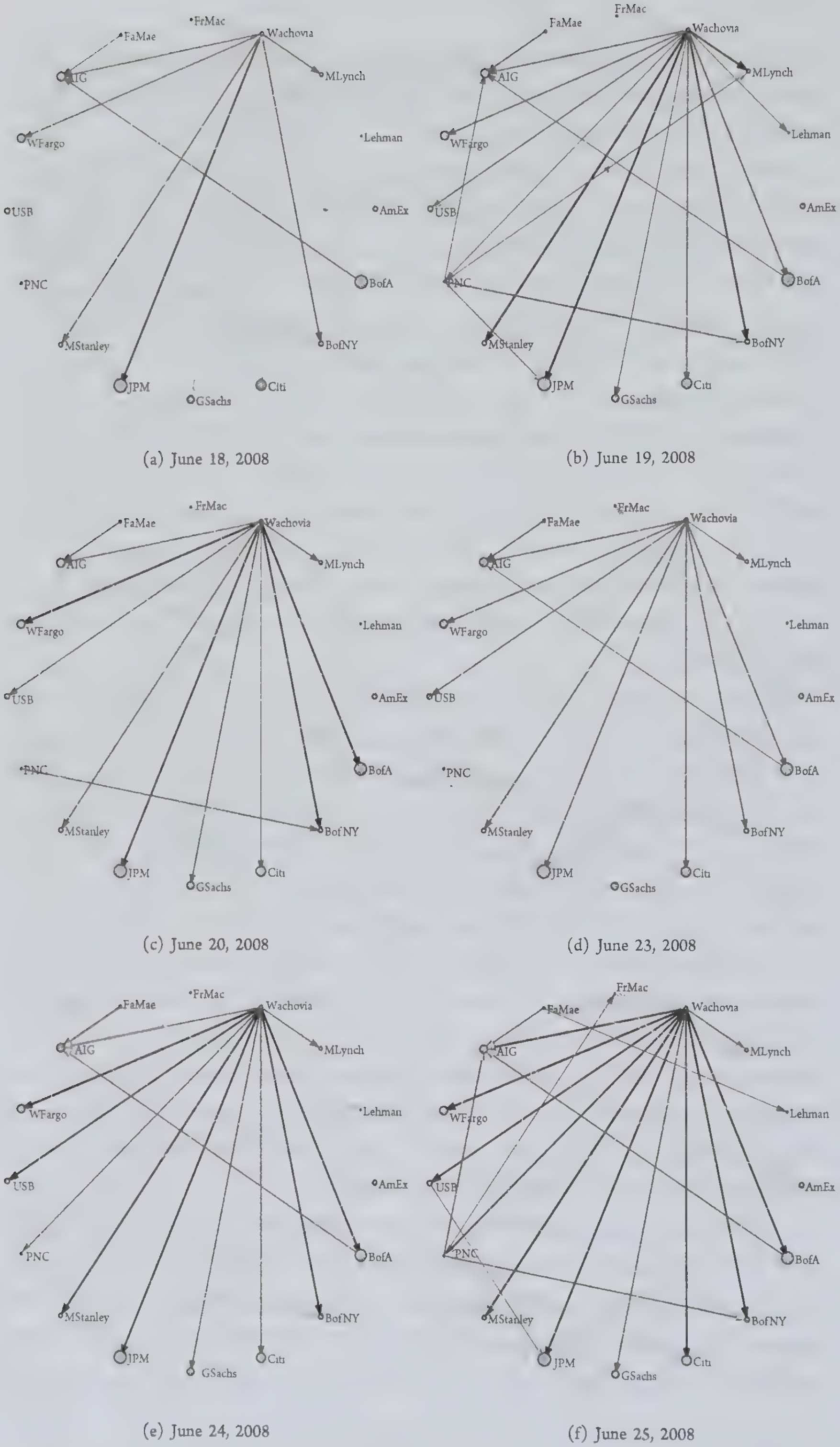
The other investment bank that was having troubles and hence would have definitely headed for bankruptcy after the Lehman Brothers was Merrill Lynch. However, the management of Merrill Lynch was able to sell the whole bank to the Bank of America hours before the announcement of the bankruptcy of the Lehman Brothers on September 15, 2008. Merrill Lynch's net directional connectedness from the beginning of the crisis until the September of 2008 never exceeded 2.5%. Merrill Lynch's net total volatility connectedness increased only after it was sold to the Bank of America and reached close to 4% in the final days of 2008 before the finalization of the deal on December 31, 2008 (see Figure 3.5).[10]

As we have already emphasized in Figure 3.5, among the six troubled banks, Wachovia was the one that had the highest net directional connectedness with other stocks. Wachovia's problems had already been known in 2007. At the heart of its troubles were its 2006 acquisition of Golden West Financial, a large California-based mortgage lender specializing in option adjustable-rate mortgages. However, as an increasing number of adjustable-rate mortgage holders were unable to make scheduled mortgage payments, Wachovia's balance sheet worsened much faster than expected. It suffered a loss of $8.9 billion in the second quarter of 2008, approximately 80% of which was due to the nonperforming loans of Golden West Financial. The board fired the CEO of the bank on June 2, 2008 as the pressure on the stock started to intensify. From June 11 onwards, Wachovia started to transmit substantial net pairwise connectedness to other financial equities. As the markets started to worry about the future of Wachovia, the net volatility transmission by the bank indeed spread almost equally to all major banks.

Wachovia's problems got worse toward the end of the month in the second half of June. From June 18 through June 25, 2008, long before the climax month (September 15–October 15) of the financial crisis, Wachovia's stock came under heavy pressure and its net pairwise connectedness with other financial stocks increased substantially to be ranked in the top one to top 10 percentile of all net pairwise connectedness measures in the second half 2008 (see the string-ball plots in Figure 3.8). Wachovia's problems did not last a couple of days. As the news about the losses mostly related to the mortgages issued by Golden West Financial continued to arrive, the stock continued to transmit volatility shocks to other bank stocks with increasing intensity, throughout July and August. As can be seen from the solid black colors of each graph, from July 9 through July 16, Wachovia was one of the most active net volatility transmitters among the financial stocks (see Figure 3.9). Furthermore, even a week before the collapse of Lehman Brothers, the net pairwise volatility connectedness of Wachovia with other banks were quite significant.

After showing how a critical role Wachovia played during the summer of 2008 with its high directional volatility connectedness, we finally focus on the first few days in the post-Lehman bankruptcy period. The net pairwise volatility connectedness plots for September 18 through 23 show how central was AIG among the remaining stocks. Based on the evidence from the pairwise net volatility connectedness plots, it

[10] The uncertainty about the eventual closure of the acquisition process at the end of the year led to an increase in Merrill Lynch's net volatility connectedness.



(a) June 18, 2008

(b) June 19, 2008

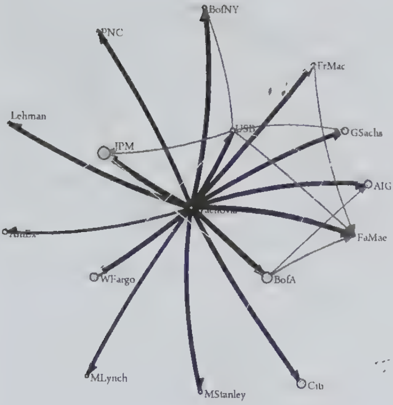
(c) June 20, 2008

(d) June 23, 2008

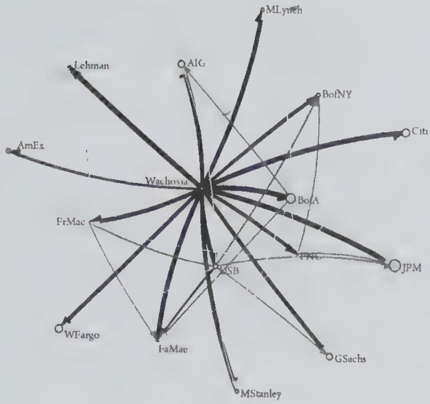
(e) June 24, 2008

(f) June 25, 2008

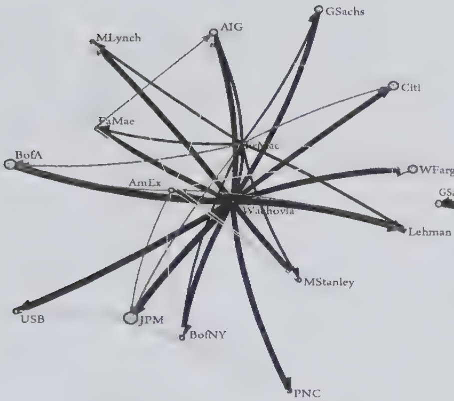
Figure 3.8 Pairwise connectedness during June 2008.
See Figure 3.6 for details.



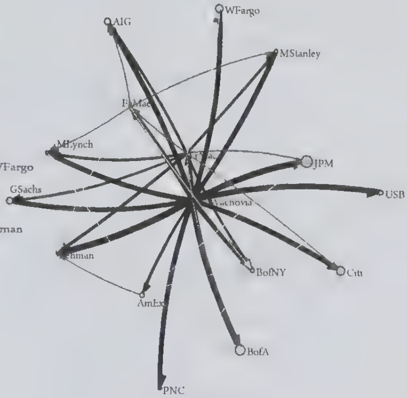
(a) July 9, 2008



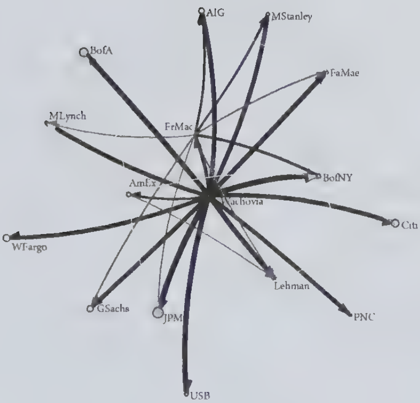
(b) July 10, 2008



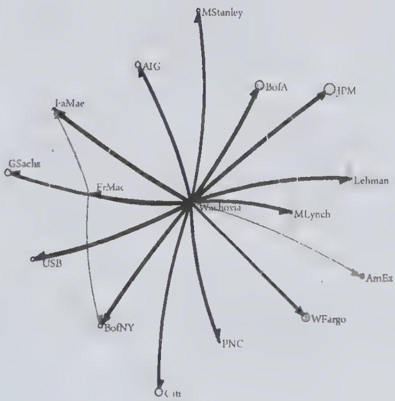
(c) July 11, 2008



(d) July 14, 2008



(e) July 15, 2008



(f) July 16, 2008

Figure 3.9 Pairwise connectedness during July 2008.
See Figure 3.6 for details.

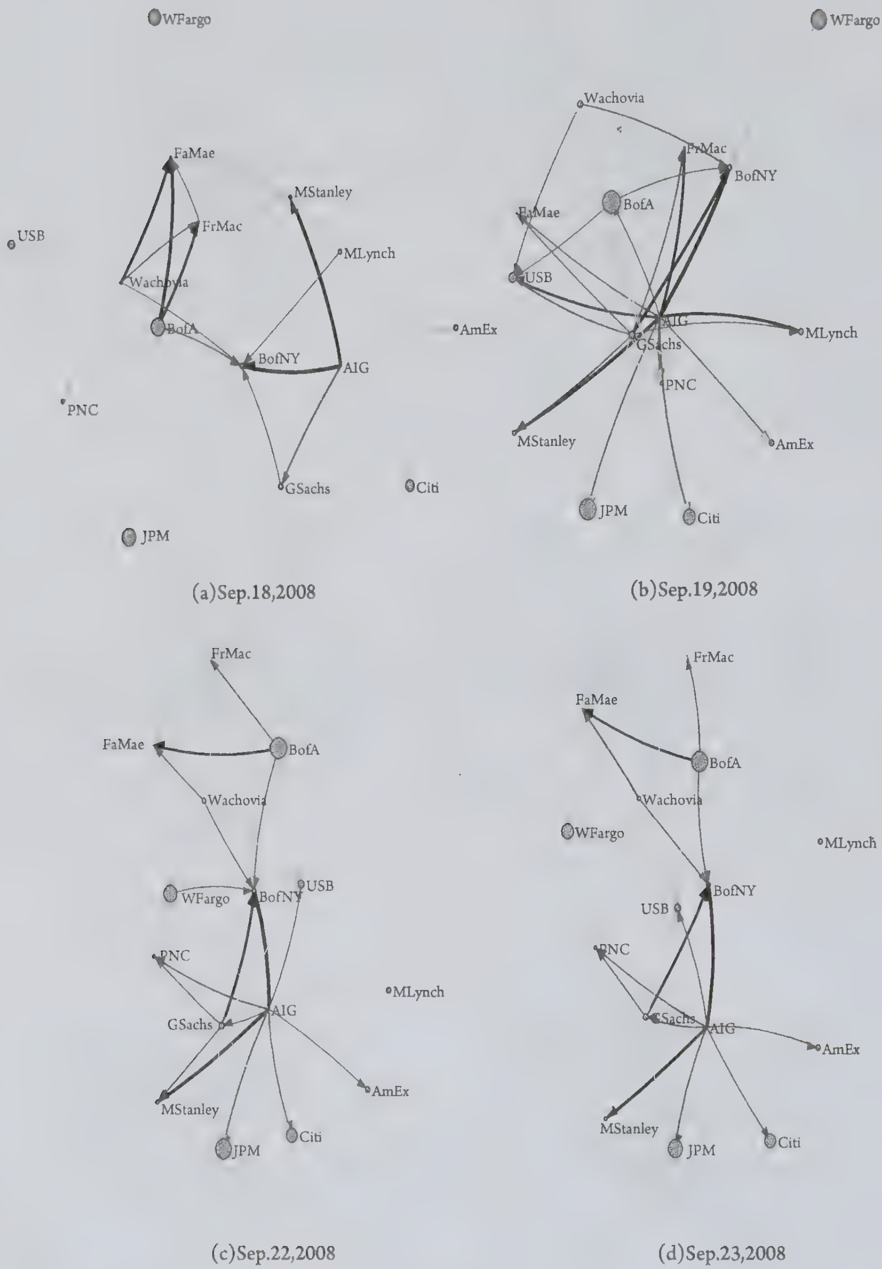


Figure 3.10 Pairwise connectedness during September 2008.
See Figure 3.6 for details.

is possible to assert that the U.S. Treasury was right to prevent the collapse of the AIG after the collapse of Lehman Brothers. Even though the markets learned about the Injection of $85 billion (by the U.S. Treasury and the Fed) on the morning of September

16, AIG continued to be at the center of all net pairwise volatility connectedness plots for September 18 through 23 (Figure 3.10). Its net total connectedness continued to run high from late September through November 2008 (Figure 3.5).

3.A APPENDIX: STANDARD ERRORS AND ROBUSTNESS

We again delegated the presentation and a brief discussion of the standard errors of the total volatility connectedness table and the robustness analysis to the Appendix. Table 3.A.1 presents the volatility connectedness table with standard errors.

The total and all pairwise directional connectedness measures are statistically different from zero at the 1% level. All directional "to" and "from" connectedness measures are also statistically different from zero. The "net" directional connectedness measures for American Express Bank, Bank of New York Mellon, J.P. Morgan, Morgan Stanley, U.S. Bancorp, Wells Fargo, and Freddie Mac are not statistically different from zero. The remaining six banks either have positive or negative "net" volatility connectedness with other banks.

The robustness assessment of this chapter is slightly more involved than the ones we conduct in other chapters. In this appendix, we plot the total connectedness for two alternative identification methods (namely, the Cholesky factor identification and the generalized identification), for alternative values of the window width (in addition to $w = 100$ days, we consider 75- and 125-day long sample windows), and for alternative forecast horizons (in addition to $H = 12$ days, we consider 6 and 18 days). The results are presented in Figure 3.A.1. In each plot, the solid line is the total connectedness measure obtained through the generalized identification for each value of H and w. In the case of Cholesky factor identification, we calculate the connectedness index for 100 random orderings of the realized stock return volatilities. The gray band in each plot corresponds to the (10%, 90%) interval based on these 100 randomly selected orderings.

In all subgraphs, the solid line that corresponds to the generalized identification-based total connectedness measure runs higher than the gray band that corresponds to the Cholesky identification. As the generalized identification treats each variable to be ordered as the first variable in the VAR system, the total connectedness obtained from generalized identification is never less than the one obtained from the Cholesky-based identification. Nevertheless, in all subgraphs of Figure 3.A.1, the two series move very much in accordance over time, a strong indication of the robustness of our total connectedness measures based on generalized identification. It is also important to note that the (10%, 90%) interval based on 100 random orderings of the Cholesky-based total connectedness is quite narrow. The ordering of the financial stocks in the VAR do not really matter much to follow the dynamic behavior of total connectedness.

Table 3.A.1 Volatility Connectedness Table, Major U.S. Financial Institutions (100-Day Window)

	AXP	*BAC*	*BK*	*C*	*GS*	*JPM*	*MS*	*PNC*	*USB*	*WFC*	*AIG*	*FNM*	*FRE*	*FROM*
AXP**	20.0	8.5	7.1	10.3	5.8	9.8	8.8	5.1	8.0	7.8	3.2	2.6	3.0	80.0
	(1.09)	(0.71)	(0.69)	(0.78)	(0.66)	(0.68)	(0.72)	(0.62)	(0.70)	(0.74)	(0.56)	(0.48)	(0.52)	(1.09)
BAC**	8.3	19.1	6.0	10.6	5.8	8.0	7.4	6.1	7.1	9.2	4.2	3.5	4.6	80.9
	(0.69)	(0.98)	(0.62)	(0.76)	(0.63)	(0.61)	(0.65)	(0.65)	(0.65)	(0.71)	(0.61)	(0.54)	(0.62)	(0.98)
BK**	8.4	8.3	18.8	8.4	6.2	9.3	8.5	5.7	8.4	8.3	4.2	2.4	3.0	81.2
	(0.69)	(0.66)	(0.97)	(0.68)	(0.64)	(0.64)	(0.69)	(0.60)	(0.68)	(0.68)	(0.61)	(0.44)	(0.50)	(0.97)
C**	9.5	9.6	5.4	20.4	4.9	8.7	7.8	5.2	7.0	8.0	5.4	3.5	4.7	79.6
	(0.75)	(0.74)	(0.62)	(1.10)	(0.61)	(0.67)	(0.68)	(0.62)	(0.67)	(0.73)	(0.69)	(0.55)	(0.64)	(1.10)
GS**	8.2	8.6	6.8	7.6	22.1	8.8	13.3	4.0	6.0	7.6	2.4	1.9	2.6	77.9
	(0.71)	(0.71)	(0.69)	(0.69)	(1.17)	(0.66)	(0.83)	(0.60)	(0.66)	(0.71)	(0.48)	(0.41)	(0.50)	(1.17)
JPM**	10.2	8.6	7.1	10.6	6.2	18.8	9.5	5.2	7.8	7.3	3.6	2.5	2.6	81.2
	(0.74)	(0.68)	(0.65)	(0.75)	(0.65)	(0.87)	(0.70)	(0.59)	(0.66)	(0.72)	(0.56)	(0.45)	(0.47)	(0.87)
MS**	9.2	8.3	7.1	8.9	9.8	9.7	20.5	4.2	5.5	7.1	3.4	2.8	3.6	79.5
	(0.73)	(0.68)	(0.69)	(0.72)	(0.73)	(0.67)	(1.06)	(0.58)	(0.61)	(0.68)	(0.57)	(0.50)	(0.57)	(1.06)
PNC**	7.7	8.8	7.4	8.5	4.6	7.6	6.6	18.1	7.6	8.8	5.2	4.2	4.9	81.9
	(0.64)	(0.67)	(0.62)	(0.67)	(0.56)	(0.58)	(0.60)	(1.04)	(0.63)	(0.68)	(0.63)	(0.56)	(0.60)	(1.04)

USB**	9.3	9.9	7.6	9.9	5.7	8.7	6.4	5.4	20.1	8.5	4.3	1.6	2.7	79.9
	(0.76)	(0.76)	(0.68)	(0.76)	(0.67)	(0.64)	(0.66)	(0.63)	(1.12)	(0.76)	(0.62)	(0.38)	(0.51)	(1.12)
WFC**	8.3	10.2	6.5	9.8	6.2	7.6	7.1	5.9	7.3	18.0	3.8	3.8	5.3	82.0
	(0.68)	(0.72)	(0.62)	(0.73)	(0.62)	(0.60)	(0.62)	(0.62)	(0.64)	(0.95)	(0.57)	(0.55)	(0.63)	(0.95)
AIG**	5.3	7.3	4.9	8.8	2.6	5.2	4.9	6.2	6.0	5.6	27.5	6.6	9.0	72.5
	(0.72)	(0.82)	(0.70)	(0.86)	(0.52)	(0.66)	(0.71)	(0.77)	(0.76)	(0.71)	(1.90)	(0.88)	(0.99)	(1.90)
FNM**	4.2	5.4	2.5	6.0	2.3	3.5	3.8	5.5	1.9	6.8	6.5	29.6	22.0	70.4
	(0.68)	(0.81)	(0.55)	(0.82)	(0.53)	(0.59)	(0.66)	(0.80)	(0.50)	(0.84)	(0.95)	(1.81)	(1.51)	(1.81)
FRE**	4.3	6.3	2.9	6.5	2.6	3.3	4.1	5.2	2.9	7.3	7.4	17.6	29.6	70.4
	(0.69)	(0.85)	(0.60)	(0.83)	(0.58)	(0.58)	(0.67)	(0.78)	(0.60)	(0.83)	(1.00)	(1.39)	(1.95)	(1.95)
TO**	92.9	99.7	71.3	106.1	62.7	90.2	88.2	63.7	75.5	92.2	53.8	53.1	68.1	**78.3**
	(6.98)	(7.16)	(6.41)	(7.33)	(6.18)	(6.19)	(6.59)	(6.38)	(6.35)	(7.10)	(6.46)	(5.69)	(6.29)	
NET	13.0	18.8**	−9.9	26.5**	−15.2*	8.9	8.7	−18.2**	−4.4	10.2	−18.7**	−17.4**	−2.3	78.3**
	(7.59)	(7.69)	(6.81)	(8.00)	(6.38)	(6.60)	(7.12)	(6.62)	(6.86)	(7.48)	(7.16)	(6.35)	(7.09)	(0.80)

Notes: The sample is from May 4, 1999 through April 30, 2010. Nonparametrically bootstrapped standard errors (5000 drawings) are presented in parentheses. ** and * indicate significance (based on bootstrapped standard errors that are not presented here to save space) at the 1% and 5% levels, respectively. ** next to the row heading indicates that all entries of the row are significantly different from zero at the 1% level.

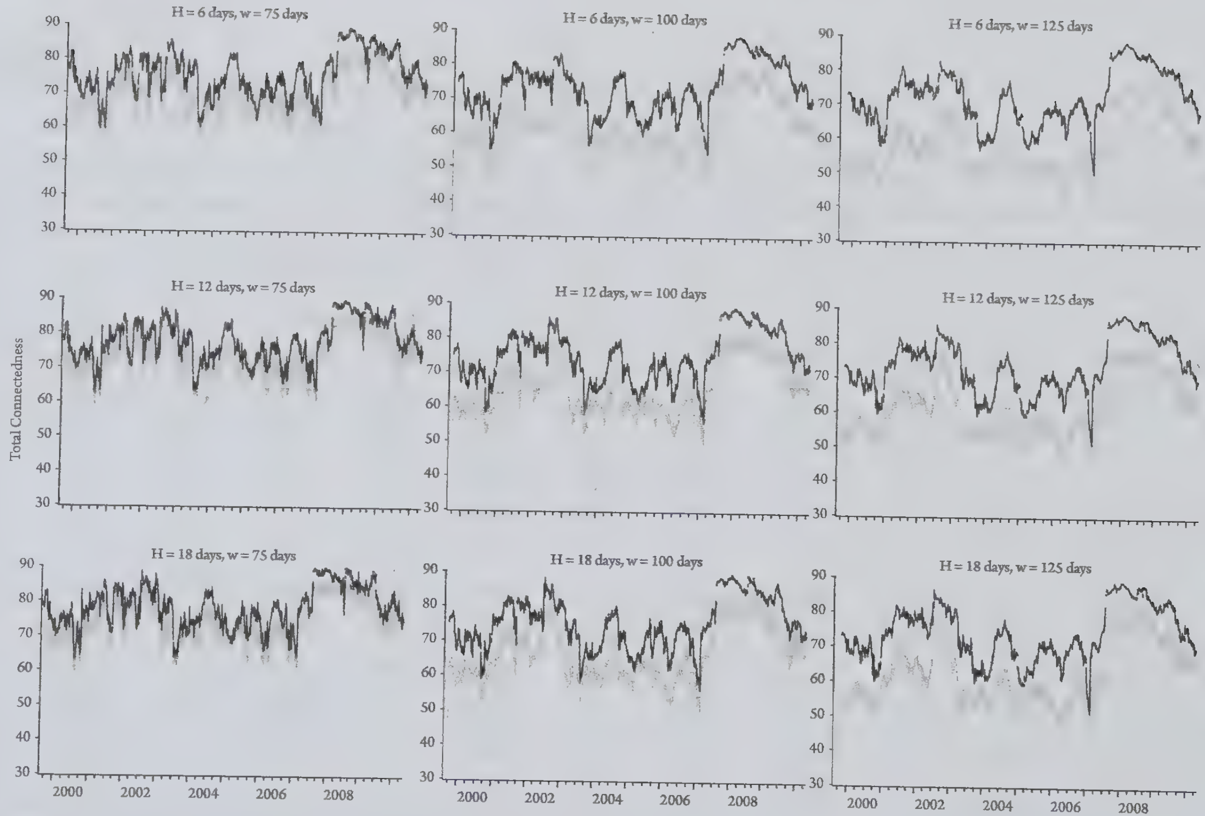


Figure 3.A.1 Robustness of total volatility connectedness, major U.S. financial institutions.
We explore estimation window widths w of 75, 100, and 125 days, forecast horizons H of 6, 12, and 18 days, and a variety of Cholesky orderings. In each subgraph, the solid line corresponds to our benchmark ordering, and the gray band corresponds to a [10%, 90%] interval based on 100 randomly selected orderings.

As the window length, w, is increased, the gap between total connectedness based on the generalized identification and the one based on the Cholesky identification increases. Both connectedness measures are more wiggly when the window width is set to 75 days, but become smoother as we increase the window width to 125 days. Similarly, given the window length, a shorter forecast horizon, H, implies a smaller gap between the generalized and Cholesky-based total connectedness measures.

To summarize, our robustness checks show that the dynamic behavior of the total connectedness measures over the rolling-sample windows is robust to the choice of alternative sample window lengths, forecast horizons, identification methods, and orderings of stocks in the VAR system.

4

GLOBAL STOCK MARKETS

We are not interdependent but everybody is interconnected.

[Kamal Nath, Minister for Urban Development, India, video interview with Financial Times, January 27, 2011.]

We start our analysis of connectedness across global financial markets with stock markets. As one of the most important sources of finance for companies, the stock market plays a central role in market economy. Stocks are priced based on expected future cash flow, which in turn is closely linked to economic activity. The resulting forward-looking perspective makes the stock market the most important barometer of current and expected future economic activity.

Another reason for starting with an analysis of stock markets is purely for convenience. If one wants to include emerging financial markets in the analysis of the return and volatility connectedness with daily data, one has to start with the stock market. Despite having lower market capitalization and market liquidity than their counterparts in developed economies, stock markets in many emerging market economies are functioning properly. In addition, intra-day data that are needed to calculate the daily range or realized volatility measures have been available for these markets since the early 1990s. In the case of bond markets in emerging market economies, however, intra-daily data were not available until recently. Furthermore, before the first half of 2000s, many emerging market economies have followed fixed or managed exchange rate regimes which rule out the determination of exchange rates by market forces.

The early literature on the interdependence of international stock markets finds that the United States led major stock markets around the world both in returns and in volatility of returns (see King and Wadhwani (1990), Hamao et al. (1990), Lin et al. (1994), and King et al. (1994)). Another important result of the literature concerns the increased interdependence during times of high volatility (see Roll (1989) and Longin and Solnik (2001)). As a result, when markets are going through a period of high uncertainty, their interdependence tends to increase. This finding is important because in periods of high volatility, the benefits of international stock market diversification decline, since the correlation between the major stock market returns tends to be higher during periods of high volatility.

Unlike the previous literature, in this chapter we are going to analyze return and volatility connectedness across stock markets separately. We start the chapter with a brief overview of the global equity markets, followed by a description of the data in Section 4.1. After reporting the full-sample connectedness analysis in Section 4.2, we present the dynamic connectedness analysis in Section 4.3.

4.1 RETURN AND VOLATILITY IN GLOBAL STOCK MARKETS

In the analysis of global stock markets we include 10 major stock markets around the world. The list includes six industrial countries (the United States, the United Kingdom, France, Germany, Japan, and Australia) and four emerging market economies (Brazil, China, India, and Hong Kong). We choose these countries on the basis of market capitalization of their respective stock markets. In 1996, these countries' stock markets accounted for 81% of the global stock market capitalization. Even though their global stock market share declined over time, it was 74% as of the end of 2012 (see Table 4.1).

The underlying data are daily nominal local-currency stock market indexes, from January 1994 to June 2013, taken from Yahoo Finance and Bloomberg. We calculate daily returns as the change in daily log closing prices. When the market is closed on a particular day, we substitute the missing value with the previous day's return, if the majority of the stock markets in our sample are open that day. We provide a variety of descriptive statistics for annualized returns in Table 4.2. Japan is the only country with a negative mean return. Brazil, China, and India have the highest mean returns, followed by Germany and the United States.[1] Brazil and China are the countries that have the highest maximum and minimum daily returns in absolute value.

[1] In the case of Brazil, higher nominal returns is mostly due to the country's high inflation rates in the earlier part of the sample. In Diebold and Yilmaz (2009), where we used weekly stock return data for 19 stock markets, we corrected the returns data for possible inflation effects and focused on

Table 4.1 Market Capitalization of Stock Markets (End-of-Year Values in Billion USD)

	1996	*2012*		*1996*	*2012*
United States	8,452	18,668	Australia	312	1,263
United Kingdom	1,643	3,397	Hong Kong	449	2,832
Germany	665	1,486	China	463	3,697
France	1,106	2,832	India	130	1,263
Japan	3,011	3,681	Brazil	217	1,227
Total MC	**15,854**	**35,126**	**Global Share (%)**	**81**	**74**

Notes: The data are from the World Federation of Exchanges. The U.S. data are the total for the NYSE, NASDAQ, and AMEX stock exchanges (SEs). The French data are for the Euronext (Europe), which incorporates the Paris, the Amsterdam, and the Brussels SEs. The Chinese and Indian data under the 1996 column are actually for the end of 2002. The Chinese data are the total for Shanghai and Shenzhen SEs. The Japanese data are the total for Tokyo and Osaka SEs. The Global Share is the combined market capitalization share of the 10 stock markets in the 52-member World Federation of Exchanges.

Table 4.2 Annualized Returns—Descriptive Statistics (January 4, 1994–June 28, 2013)

	United States	*United Kingdom*	*Germany*	*France*	*Japan*
Mean	9.2	5.5	9.3	3.8	−1.2
Median	23.6	20.4	34.4	14.9	4.2
Maximum	3999.4	3425.2	3941.1	3867.0	4830.6
Minimum	−3456.4	−3381.6	−3236.8	−3457.1	−4420.5
Std. Dev.	447.5	432.3	552.8	534.4	559.0
Skewness	−0.233	−0.145	−0.121	−0.008	−0.334
Kurtosis	10.972	8.754	7.268	7.356	8.778
	Australia	*Hong Kong*	*China*	*India*	*Brazil*
Mean	6.2	6.9	21.1	13.1	40.2
Median	17.9	19.5	27.7	27.8	51.5
Maximum	2214.3	6295.2	10534.0	5836.3	10523.9
Minimum	−3122.1	−5378.1	−6535.4	−4310.4	−6281.0
Std. Dev.[a]	350.6	630.5	742.3	595.0	860.4
Skewness	−0.550	0.058	1.154	−0.040	0.483
Kurtosis	9.516	11.741	25.935	8.245	13.560

[a]Std. Dev., standard deviation.

real returns only. Since our analysis here relies only on daily data, we do not need to adjust daily returns for inflation. India and China also had inflation rates slightly higher than those of the industrial countries. We do not make any corrections in their daily returns, either.

Then, following Garman and Klass (1980) and Alizadeh et al. (2002), we can use the difference between the natural logarithms of daily high, low, opening, and closing prices to obtain the range estimate of the daily stock return volatility:

$$\tilde{\sigma}_{gk}^2 = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) \\ -2(h-o)(l-o)] - 0.383(c-o)^2, \tag{4.1}$$

where h, l, o and c are, respectively, the natural logarithms of daily high, low, opening, and closing prices in market i on day t (not shown in the formula).

We present the descriptive statistics for annualized volatilities in Table 4.3. The mean volatility over the full sample tends to be higher than the median volatility, reflecting in part the significant impact of the high volatility days on the full-sample mean. Given that all markets lived through the worst market uncertainty during the global financial crisis, it would not be wrong to observe that the maximum volatility values were realized during the global financial crisis.

As expected, Brazil stands out as the country with the highest mean, median, and maximum daily range volatility for the period from December 1996 to June 2013. In terms of the size of the mean and median range volatility, Brazil is followed by India,

Table 4.3 Annualized Range Volatility—Descriptive Statistics (December 4, 1996–June 28, 2013)

	United States	*United Kingdom*	*Germany*	*France*	*Japan*
Mean	16.08	16.71	21.18	19.44	17.12
Median	13.41	14.01	17.80	16.68	15.04
Maximum	147.31	133.62	142.40	123.55	149.72
Minimum	2.40	1.33	1.64	2.84	2.97
Std. Dev.[a]	10.89	10.89	14.08	11.77	10.00
Ln Skewness	0.252	0.129	0.003	0.111	0.092
Ln Kurtosis	3.317	3.263	3.175	3.157	3.340
	Australia	*Hong Kong*	*China*	*India*	*Brazil*
Mean	10.69	18.16	20.47	21.21	27.35
Median	9.00	15.37	17.06	17.95	22.94
Maximum	167.36	194.10	122.80	193.55	312.25
Minimum	1.65	3.31	0.70	4.59	4.09
Std. Dev.	7.48	11.75	12.80	13.28	18.50
Ln Skewness	0.330	0.301	0.254	0.407	0.409
Ln Kurtosis	3.769	3.257	3.501	3.328	4.161

[a] Std. Dev., standard deviation.

Germany, China, and France. While one would expect India and China to have high stock market return volatility like the other emerging markets in our sample, it is surprising to see that Germany had stock return volatility higher than other industrial countries and as high as that of China and India over the full sample period.

We present the kernel density estimates of the log range volatility in Figure 4.1. Kernel density estimates follow the theoretical kernel density of a normal distribution

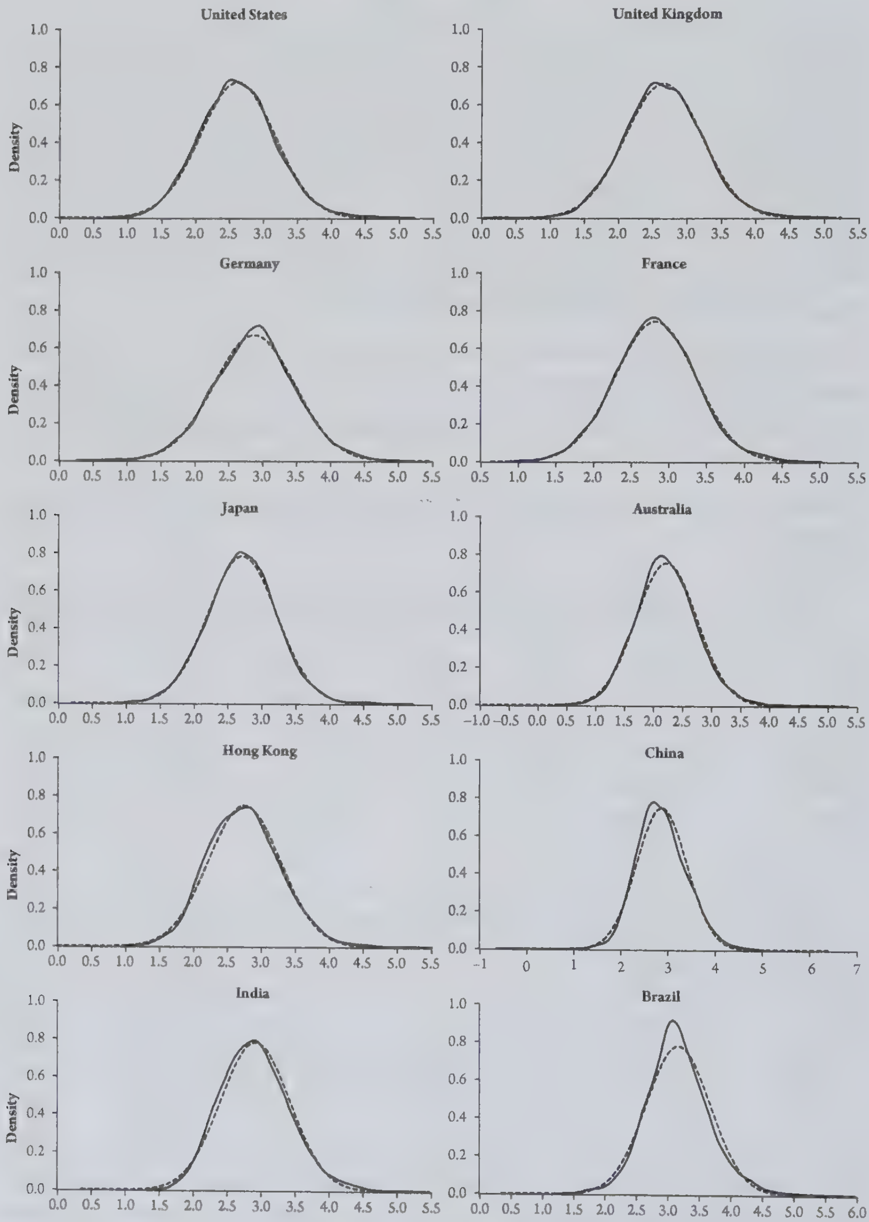


Figure 4.1 Log range volatility–kernel density estimates (compared with $N(0,1)$).

quite closely. Brazil is the country for which the kernel density estimate of the log range volatility deviates from that of a normal distribution the most.

4.2 FULL-SAMPLE RETURN AND VOLATILITY CONNECTEDNESS

4.2.1 Total Return and Volatility Connectedness

In this section, we provide the full-sample analysis of the connectedness of global stock market returns and volatility. We begin by characterizing return and volatility connectedness over the December 1996–June 2013 sample in Tables 4.4 and 4.5, respectively. Subsequently, we will track time variation in connectedness via a rolling window estimation. Even though daily returns data are available for all countries in our sample starting from December 1990, we limit the full-sample analysis to the December 1996–June 2013 period because the daily high, low, opening, and closing price data are available only from December 1996. When we analyze the dynamics of connectedness, we will extend the sample period to include January 1994 through November 1996 in the sample as well.[2]

Table 4.4 Return Connectedness Table, 10 Major Stock Markets

	USA	*UK*	*GER*	*FRA*	*JPN*	*AUS*	*HKG*	*CHN*	*IND*	*BRA*	*FROM*
USA	42.3	13.4	14.6	13.6	0.8	1.5	2.0	0.0	1.3	10.4	57.7
UK	13.2	32.9	18.0	21.9	1.6	2.2	3.1	0.1	1.7	5.3	67.1
GER	13.4	18.4	33.6	22.5	1.2	1.8	2.9	0.1	1.3	4.7	66.4
FRA	12.8	21.6	21.7	32.0	1.3	1.7	2.5	0.1	1.5	4.9	68.0
JPN	11.7	8.8	8.2	8.7	45.3	5.2	5.4	0.3	2.1	4.5	54.7
AUS	16.4	11.3	9.4	10.3	3.7	32.9	5.8	0.4	2.5	7.3	67.1
HKG	10.8	8.5	6.9	7.0	4.9	7.1	43.2	1.6	4.0	6.0	56.8
CHN	0.6	0.7	0.6	0.6	0.6	1.1	3.5	90.6	1.2	0.4	9.4
IND	4.7	4.5	3.9	4.2	1.7	3.2	5.7	0.7	68.2	3.2	31.8
BRA	14.1	8.1	7.1	7.6	0.9	1.5	2.2	0.1	1.4	57.0	43.0
TO	97.8	95.1	90.4	96.3	16.6	25.4	33.1	3.4	17.0	46.6	
NET	40.1	28.0	24.0	28.3	−38.0	−41.7	−23.7	−5.9	−14.8	3.7	**52.2**

Notes: The sample is taken from January 3, 1994 through June 28, 2013. All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in this chapter's appendix, in Table 4.A.1.

[2] We limited our sample for returns to 1994 and after, and for volatility to December 1996 and after, because data for the Chinese stock market returns are not available for the period before 1994. We

Table 4.5 Volatility Connectedness Table, 10 Major Stock Markets

	USA	*UK*	*GER*	*FRA*	*JPN*	*AUS*	*HKG*	*CHN*	*IND*	*BRA*	*FROM*
USA	46.9	12.7	13.2	13.0	1.8	2.5	3.0	0.1	0.6	6.3	53.1
UK	12.5	40.1	19.4	18.0	0.9	2.9	3.0	0.1	0.4	2.8	59.9
GER	11.2	16.3	44.5	21.5	0.9	0.9	1.9	0.1	0.0	2.7	55.5
FRA	12.9	18.0	23.7	38.3	0.9	1.8	2.2	0.0	0.1	2.0	61.7
JPN	8.1	4.1	4.5	5.0	65.2	1.9	5.8	0.2	1.3	3.9	34.8
AUS	10.5	10.8	4.2	5.7	1.5	56.4	5.0	1.9	1.1	2.9	43.6
HKG	7.2	6.8	2.8	3.2	3.0	2.9	64.8	1.1	4.1	4.2	35.2
CHN	0.5	0.3	0.1	0.1	0.4	2.0	1.7	93.6	0.9	0.5	6.4
IND	4.2	2.4	0.7	0.7	1.6	1.0	7.9	0.6	77.6	3.2	22.4
BRA	11.6	6.0	5.8	4.0	1.7	1.2	5.5	0.0	1.2	63.0	37.0
TO	78.6	77.3	74.3	71.1	12.7	17.0	35.9	4.2	9.7	28.6	
NET	25.5	17.5	18.8	9.4	−22.1	−26.6	0.7	−2.2	−12.6	−8.4	**41.0**

Notes: The sample is taken from December 4, 1996 through June 28, 2013. All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in this chapter's appendix, in Table 4.A.2.

Tables 4.4 and 4.5 contain valuable information on several layers of return and volatility connectedness.

The key substantive result to emerge from Tables 4.4 and 4.5 is that, distilling all of the various forms of cross-country connectedness into a single connectedness index for our full 1996–2013 data sample, we find that close to half of the forecast error variance comes from connectedness, both for volatility (41.0%) and returns (52.2%). Hence, connectedness is important for both returns and volatility; and, on average—that is, unconditionally—return connectedness exceeds volatility connectedness for the group of major stock markets in our sample.

While global stock markets are highly connected, they are not as connected as the major American financial institutions: The total volatility connectedness of global stock markets, 41%, is much lower than the total return connectedness of the major American financial institution stocks, 78.3% (see Chapter 3).

The difference between the total return and volatility connectedness reflects the increased interdependence across markets over time. With globalization spreading to different parts of the world, global capital flows have increased substantially over time and global stock markets have become more connected. Whether the major

decided that we could not leave the Chinese stock market out of an analysis of the connectedness of global stock markets.

economies of the world are in expansion or recession, the stock market indices tend to move in sync as they become more integrated. In other words, the more likely it is that positive or negative return shocks will spread to other markets, the more the stock markets are integrated. Volatility connectedness, on the other hand, does not necessarily reflect the increased interdependence over time. Volatility connectedness across markets does not have to be high in periods of tranquility. This is true even when markets are highly integrated, as was the case between 2003 and 2006. Since financial crises are characterized by shocks to volatility, volatility connectedness tends to become a major phenomenon during such crises. There were quite a few financial crises around the world over the full sample of our analysis; nevertheless, crisis periods represent only a small fraction of the time period covered by our sample. Global stock markets went through more tranquil times over a larger portion of our sample. Hence, in the full-sample analysis, we would not expect volatility connectedness to be higher than return connectedness. However, as we will see later, during times of crises, volatility connectedness is likely to increase more significantly than return connectedness.

4.2.2 Directional Return and Volatility Connectedness

Starting with returns, the total "to" and "from" directional connectedness of each country is presented in the corresponding "TO" row and the "FROM" row in Table 4.4. The most striking result of the total directional connectedness measures is that the Western market economies in our sample—namely, the United States, the United Kingdom, Germany, and France—differentiate themselves from others by having very high "to" connectedness, ranging between 90% and 98%. They also have high "from" connectedness, but it is not as high as their "to" connectedness. As a result, their net connectedness measures are all positive and range between 24% and 40%. Shocks to stock returns in the United States, the United Kingdom, Germany, and France, therefore, have a substantial indirect impact on stock returns in other countries.

At the other end of the spectrum, the Chinese and Indian stock markets appear to be the least connected in returns among the 10 major markets we considered. They stand out with their low "to" connectedness, 3.4% and 17%, respectively, and low "from" connectedness, 9.4% and 31.8%, respectively, over the full sample. Their net directional connectedness measures are also among the lowest in absolute value and show that they are net recipients of shocks from others. Brazil also has low net connectedness (3.7%). Yet, the fact that Brazil's net connectedness for the full sample is positive implies that Brazil generated connectedness to other countries rather than being influenced by shocks originated in other countries. In addition, Brazil's "to" and "from" connectedness measures indicate that, unlike China and India, it was highly connected throughout the period. Its "to" connectedness exceeded that of Japan, Australia, and Hong Kong, countries whose capital markets are more liquid, better capitalized, and more open than Brazil in the 1990s.

Stock markets in Japan, Hong Kong, and Australia fall in the middle range. They have high "from" connectedness, ranging from 54.7% to 67.1%, most of which are generated by the top four stock markets, but have low "to" connectedness, ranging from 16.6% to 33.1%. As the big differences between their "from" and "to" connectedness indicate, their net connectedness measures are all negative and among the largest in absolute value. The pairwise directional connectedness measures for these countries reveal that most of the "from" connectedness of these countries is generated by the largest and most developed Western stock markets, namely those of the United States, the United Kingdom, Germany, and France. Being the hub stock market for East Asia, Hong Kong generates more "to" connectedness than Japan and Australia (see the pairwise directional connectedness measures of these countries in their respective columns).

It is interesting to note that the Tokyo stock exchange, the second best capitalized and most liquid stock market in the 1990s and early 2000s, was mostly influenced by shocks to other stock markets, whereas shocks to the Tokyo stock exchange were much less relevant for other stock markets. We think that this is, in part, a result of Japan's financial crisis in the early 1990s and its ensuing recession, which lasted close to a decade. As Japan had a hard time emerging from its long recession, the rest of the world became more and more indifferent to developments in the Japanese financial markets.

A detailed look at the full-sample connectedness table for stock returns revealed some interesting results. Next, we would like to see whether these observations carry over to the case of stock return volatilities. The full sample volatility connectedness table (Table 4.5) differs from the return connectedness table (Table 4.4) in several respects, but it also has many similarities in some other respects.

Turning to the directional connectedness measures, an overwhelming majority of the stock markets in our sample have total directional connectedness ("to," "from," and "net") measures that are *lower* for volatility in absolute value terms than for returns. The "to" connectedness of Hong Kong and China and the "net" connectedness of Brazil are the only exceptions to the above observation. This observation is consistent with a lower total connectedness measure for volatility than for returns. It is also consistent with the fact that volatility connectedness tend to be lower in "good" times, whereas the return connectedness can be high during both the "good" and the "bad" times.

In terms of directional connectedness, we have three groups of countries. The four Western developed stock markets have the highest "to" and "from" volatility connectedness. As is the case with returns, they have positive "net" volatility connectedness. The "to" volatility connectedness of all four Western developed stock markets is 16–25 points lower than their respective "to" return connectedness. While their "to" return connectedness ranges from 90.4% to 97.8%, their "to" volatility connectedness ranges from 71.1% to 78.6%. Among the remaining six countries, only in the case of China and Hong Kong do the "to" volatility connectedness measures exceed the corresponding "to" return connectedness.

Japan, Australia, and Hong Kong continue to be in the middle range in terms of "from" connectedness. Japan's and Australia's "to" volatility connectedness measures are significantly lower than their "from" volatility connectedness measures. As a result, they continue to have negative "net" volatility connectedness. In contrast, Hong Kong's "to" volatility connectedness is slightly higher than its "from" connectedness, which results in a "net" volatility connectedness measure of 0.7%. This, in part, reflects the role Hong Kong played during the East Asian crisis. As we showed in Diebold and Yilmaz (2009), once Hong Kong was affected by the East Asian crisis, it was very instrumental in spreading the crisis to other stock markets in the region. Another country in the middle-range group is Brazil; its volatility connectedness is lower than its return connectedness. Furthermore, Brazil's net connectedness measure for volatility is now negative, moving it to the receiving end of the volatility connectedness.

Finally, with the lowest "to" and "from" measures, India and China are the least connected markets in volatility. China's "net" volatility connectedness is close to zero, indicating that in net terms it has not been much affected by shocks to other countries' stock markets.

We now briefly focus on the distribution of "to" and "from" connectedness over the sample of 10 countries. The survivor functions for the "to" and "from" connectedness are presented in Figure 4.2. A comparison of the plots for returns and volatility is very informative. In both the returns and the volatility graphs, the survivor function for the "from" connectedness is steeper than the one for the "to" connectedness. This is a result of the fact that "from" connectedness is less dispersed than the "to" connectedness. Actually, if we leave China and India out, the "from" connectedness for returns and volatility will be steeper—that is, less dispersed. As we have discussed before, this result conforms to the definition of "from" and "to" connectedness. A shock to one of the markets will generate "to" connectedness in other markets. Since not all markets are subject to shocks simultaneously, the "to" connectedness is likely to be more dispersed. However, as the shock is transmitted to other markets, it will lead to an

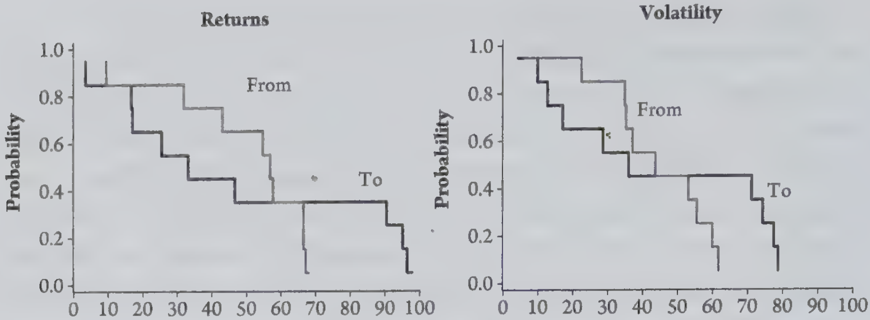


Figure 4.2 Empirical survivor functions for full-sample return and volatility connectedness.
We plot the empirical survivor functions for total directional connectedness "to" others and "from" others. The predictive horizon for the underlying variance decomposition is 12 days.

increase in "from" connectedness in other markets. As a result, "from" connectedness is likely to be less dispersed than "to" connectedness.

The divergence between the "to" connectedness for the four Western developed markets and the remaining six countries is quite visible in both the returns and the volatility graphs. While these four developed stock markets generate substantial "to" connectedness in returns and volatility, the other six countries generate much less. Since the four developed stock markets have higher market capitalization and liquidity, whenever a shock affects them, they are likely to generate a larger "to" connectedness affecting other markets. Their "from" connectedness is lower than the "to" connectedness, but still higher than the "from" connectedness of other stock markets. Since the four developed stock markets are more interconnected among each other, their "from" connectedness tends to be higher than those of other stock markets.

It is quite possible that, at any given point in time—that is, conditionally—return and volatility connectedness may be very different; and more generally, their dynamics may be very different. We now substantiate these assertions by moving from a static full-sample analysis to a dynamic rolling-sample analysis.

4.3 DYNAMICS OF RETURN AND VOLATILITY CONNECTEDNESS

4.3.1 Total Connectedness

The full-sample connectedness tables provided us with important clues about return and volatility connectedness of each of the 10 stock markets in our sample. Yet, the full-sample analysis overlooks many details that are crucial to understanding connectedness over time. In this section, we focus on the dynamics of return and

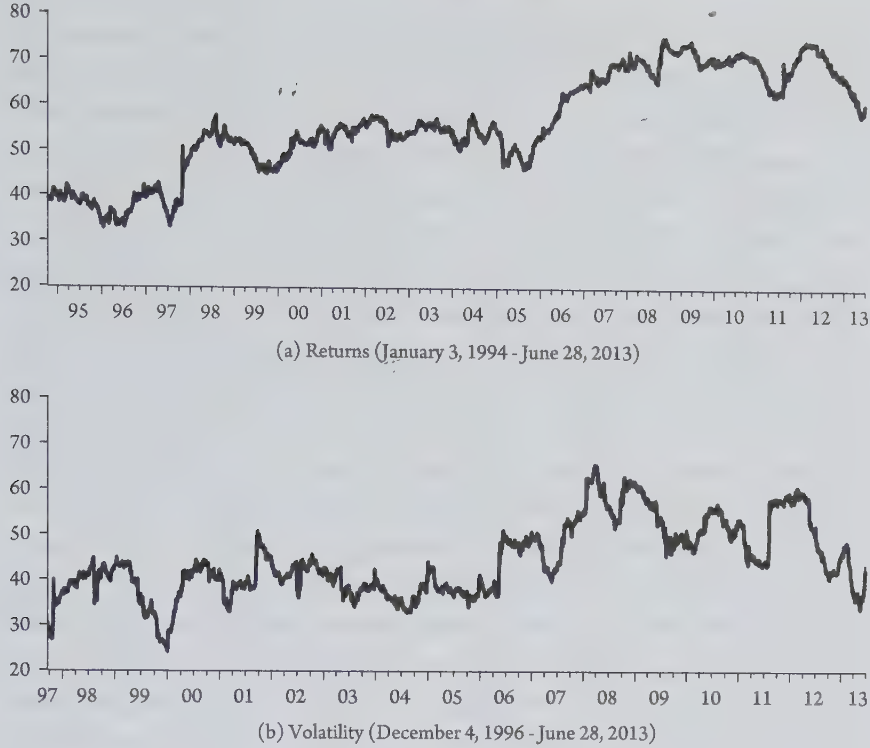


Figure 4.3 Total stock return and volatility connectedness (200-day window).

volatility connectedness over time. The dynamic analysis of connectedness is based on the total return and volatility connectedness plots presented in Figures 4.3(a) and 4.3(b), respectively.

We observe two salient features of the total return connectedness plot. First, it is relatively smooth over time. With the exception of the East Asian crisis in October 1997 and, to some extent, the Lehman Brothers' bankruptcy in September 2008, total return connectedness moves in smaller steps rather than in discrete jumps as we roll the sample windows over time. The smoothness of the return connectedness plot becomes even more striking when compared with the volatility connectedness plot.

The second important feature of the return connectedness plot is its long-term upward trend. Despite some short-term upward and downward movements, total return connectedness across global stock markets increases over time. The trend exists irrespective of what happens in the markets. The upward trend becomes even more visible when we extend the sample to include the 1994–1996 period.

To start with, the total return connectedness index was approximately 40% in 1994 and fluctuated in the 30%–40% band until the East Asian crisis of 1997. As we will see in more detail in Chapter 5, the Fed's decision to tighten monetary policy effectively helped prick the bond bubble at the time. This led to substantial return connectedness across bond markets around the world. As we can see from the directional return connectedness in Figure 4.4, the "net-connectedness" of the U.S. stock market increased from around 30% in 1994 to 70% in 1995. Other markets' "net-connectedness" did not change much over the 1994–1995 period. Most of the increase in total return connectedness in 1994 is, therefore, accounted by the U.S. stock market.

With the East Asian crisis, the connectedness jumped from 33% to 52% at the end of 1997 and continued to increase, reaching close to 60% with the development of the Russian crisis in the second half of 1998. Even though it declined to 45% in 1999, it increased again and fluctuated in the 50–60% band until mid-2006. Starting with the unwinding of the carry trade in mid-2006 and followed by the 2007–2009 financial crisis, the return connectedness gradually increased again, reaching 73% in early 2008. After a 7-percentage-point decline in the summer of 2008, the return connectedness sharply increased by 10 points following the Lehman bankruptcy in September 2008. Even though the index declined slightly to around 70% in the summer of 2009, it stayed at or above 70% thanks to the sovereign debt and banking sector troubles in the EU periphery in the first half of 2010. The index gradually came down in the first half of 2011, followed by a jump in early August 2011 as Italy and Spain were also caught in the fire. The total return connectedness index continued to increase, reaching 75% in December 2011. Following the policy moves by the ECB, the European markets stabilized and the index started to decline in mid-2012, going all the way down to 59% by the end of May 2013. The news about the Fed's possible move to taper its quantitative easing program affected the stock markets, especially the emerging stock markets, around the world and led to a slight reversal in the downward trend in June 2013.

In contrast to the return connectedness plot, there are numerous discrete jumps in the volatility connectedness plot during major market events such as the East Asian crisis in October 1997, the Russian debt crisis of August 1998, the 9/11 terrorist attacks in the United States, the WorldCom scandal of July 2002, the unwinding of the carry trades after the Federal Reserve's decision to increase interest rates in May–June 2006, the liquidity crisis of August 2007, the concentrated signs of real stress in the U.S. financial markets in late 2007–early 2008, the Lehman Brothers' bankruptcy in September 2008, and the Greek debt crisis in May 2010. After each upward discrete jump, the volatility connectedness index moved down, back to its pre-crisis levels once the rolling sample window leaves the crisis period behind, and given that there was no other shock or crisis in the meantime. The political uncertainty in Italy toward its general election led to a gradual increase in the volatility connectedness in late 2012 and early 2013. However, immediately after the Italian general elections the index went down significantly, dropping to 34% in mid-May, its lowest level since 2006. Following the Fed's announcement about the tapering of the Fed's purchases of

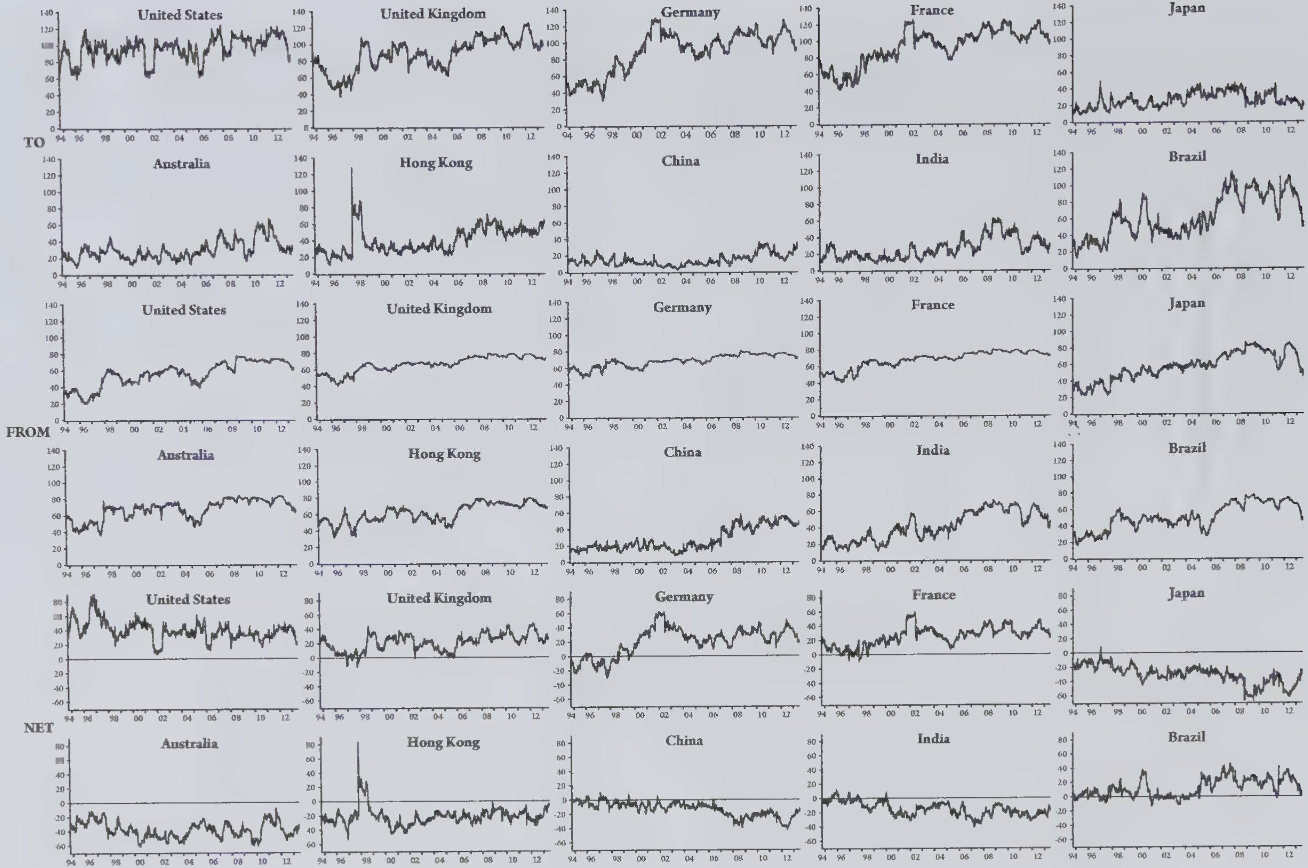


Figure 4.4 Total directional return connectedness—10 major stock markets (200-day window).

government bonds in the near future led to a reversal of capital flows from emerging markets, which is responsible for the close to 10% increase in the volatility connectedness.

The comparison of the total return and volatility connectedness plots reveals an important distinction between global stock return and volatility connectedness: Stock return connectedness retains the memory of past events, whereas volatility connectedness behaves closer to a memory-less process. After each financial crisis, the volatility connectedness jumps up. However, once the crisis episode is removed from the rolling sample window, volatility connectedness goes down, back to where it all started. The only exception is the rather long period of financial crises in the United States and the EU that lasted more than five years combined, from 2007 to the end of 2012. Thanks to recent developments in global financial markets, the total volatility connectedness is still slightly (6 percentage points) above its pre-2006 level.

The total return connectedness, on the other hand, moves as if it keeps the memory of past events intact. This is most visible in the period since 2005. Once it started increasing in 2005, its upward move continued throughout the global financial crisis. While it was 47% in late 2005, it stood at 75% in mid-2012 and 61% as of the end of our sample. A similar behavior was observed during the East Asian and Russian crises. Once the total return connectedness jumped from 39% to 50% in October 1997, over time it never moved back to the 40% level.

The comparison of the connectedness plots, therefore, reveals that while return connectedness can be used as a gauge of the interconnectedness (interdependence) of stock markets in the long run, volatility connectedness is a better instrument for understanding how interconnected stock markets become in times of crises.

To give concrete examples, let's start with the East Asian crisis. Total volatility connectedness jumps from 28% to 40% in October 1997 with Hong Kong catching the East Asian virus and stays closed to 40% as long as the data for October 1997 are included in the rolling sample. As the data for October 1997 are dropped from the sample, total volatility connectedness drops five percentage points (see Figure 4.3(b)). However, once the news of the Russian government's debt moratorium decision of August 1998 hits the markets, the total volatility connectedness jumps up again. The Russian debt crisis is followed immediately by the troubles of the Long Term Capital Management (LTCM) hedge fund in the United States in October 1998, the tremors of which were felt deeply among U.S. financial institutions and the stock market.

Before the U.S. tech-bubble burst in 2000, total volatility connectedness was as low as 24%. The tech-bubble burst first took place on the Nasdaq stock exchange and spread to other U.S. stock exchanges. As a result, total volatility connectedness increased gradually, reaching 40% by mid-2000 and staying at that level or a little lower throughout 2000 and 2001. When the 9/11 terrorist attacks took place in September 2001, total volatility connectedness jumped by 13 percentage points, reaching 51%. Since the U.S. markets were closed for a week after the attacks, most of the volatility connectedness originated from other markets; as a result, total volatility connectedness declined steadily as the sample window was rolled.

As the sample window was rolled further, from the beginning of 2002, volatility connectedness gradually increased by a couple of percentage points. This was in part due to the corporate governance scandal at Enron, a large energy, commodities, and services company, and the complacency of Arthur Andersen, one of the largest accounting firms in the world, as Enron's corporate auditor.[3] As if this was not enough, news of another corporate governance and accounting scandal broke out. This time the company involved was the second largest telecom firm in the United States, WorldCom/MCI. The index jumped by 8 percentage points in July–August 2002 following the impact of the WorldCom/MCI scandal on U.S. financial stocks.[4]

In May 2006, the index jumped close to 15 percentage points following the Fed's decision to raise the already high policy interest rate to slow down the economy and keep inflation under control. This decision had a devastating impact on many emerging stock markets, since it led to substantial capital outflows. The fact that the Fed's decision was not expected by market participants led to a significant response in the form of a sell-off in the U.S. markets followed by others, especially the emerging stock markets.

With the liquidity crisis of August 2007, total volatility connectedness increased significantly again, by close to 13 percentage points. The upward move in volatility connectedness continued in the last quarter of 2007. It was followed by another jump in January 2008, as the Fed was forced to lower the policy rate in two consecutive meetings in response to increased liquidity shortages in the market. Then, total volatility connectedness reached its highest level, 65%, in March 2008 as the Fed orchestrated J.P. Morgan's takeover of Bear Stearns.

As the markets calmed down following the successful takeover of Bear Stearns, total volatility connectedness among the global stock markets declined to 50% in July 2008. However, this brief period of tranquility proved to be rather short. First, in the first week of September 2008, Fannie Mae and Freddie Mac were taken under the conservatorship of the U.S. government. Then, Lehman Brothers went bankrupt on September 15, 2008. Volatility in the United States and other major stock markets shot

[3] After the Enron bankruptcy, in June 2002, Arthur Andersen was indicted by a grand jury for obstruction of justice in the Enron scandal. Losing all of its clients and being indicted, the firm had to be dissolved.

[4] For a more detailed discussion of the WorldCom/MCI scandal and its impact on U.S. banks, see Chapter 3.

up immediately. Volatility connectedness followed suit with an 11-percentage-point jump, to 63%. The market gyrations continued for several months.

Total volatility connectedness started to decline in early 2009 and eventually reached 45% by mid-2009 and stayed at that level until late 2009. In late 2009, market volatility started to increase again. This time around it was the Greek sovereign debt crisis that led to the jump in volatility connectedness, which took place in two stages in early March and May 2010. Volatility connectedness reached 56% by the end of June 2010. Even though it came down gradually, the fact that the Greek debt crisis was not completely resolved and Ireland and Portugal experienced similar debt sustainability problems raised total volatility connectedness above 50% by the end of 2010.[5]

The index did not stay low for too long, thanks to the increased worries about the sovereign debt and banking problems in Italy and Spain. As a result of the increased pressure on Italy and Spain throughout the summer, the index jumped from 44% at the end of July 2011 to reach 58% by August 10th. The problems of the European banks continued throughout the rest of 2011, until the new President of the European Central Bank, Mario Draghi, announced the long-term refinancing operation (LTRO) plan to provide 1 trillion euros liquidity to eurozone banks in two installments.

The connectedness index declined gradually from April through September of 2012 as the data for the trouble period of 2011 is left out of the sample window and the ECB declared in August 2012 its willingness to support the troubled countries' austerity programs through purchases of their government bonds through an operation called outright monetary transactions (OMT). As of the end of September 2012, the total volatility connectedness across the global stock markets declined to 41%.

Toward the end of 2012, the heated political debate about the U.S. fiscal policy flared up again. While Republicans proposed spending cuts to cut budget deficit, Democrats wanted to increase taxes. As the two sides could not find a compromise solution, the automatic spending cuts were expected to take place by the year's turn. The so-called "fiscal cliff" unnerved the markets. In this atmosphere the connectedness index increased gradually from 42% to 48% by the end of 2012. However, a last-minute deal was struck to provide a temporary solution before the end of the year, and the volatility connectedness of the global stock markets started to come down in the first quarter of 2013. The index went down to as low as 34% in May.

Federal Reserve Chairman Ben Bernanke's warnings on May 21 about the eventual stopping of QE policies in late 2013 and/or early 2014 led to capital outflows from

[5] In September 2010, the Irish government had to renew its guarantees for six major Irish-based banks for a third year, raising the cost of financial aid to banks to 32% of the GDP. This heavy load guaranteed to that the government had a negative impact on Irish government bonds, and so the government started negotiations with the ECB and the IMF, resulting in the 85 billion euro "bailout" agreement of November 29, 2010.

many emerging market economies in late May and June. The impact of this announcement on the volatility connectedness of the global stock markets was immediate. The index went up from 34% on May 21 to 43% by the end of June 2013, which happens to be the end of our sample.

4.3.2 Total Directional Connectedness

We now focus on the directional return and volatility connectedness measures. A comparison of the total directional connectedness plots for returns and volatility (Figures 4.4 and 4.5) reveals that the results we obtained for the total connectedness indices carry over to the directional connectedness measures. First, for each of the stock markets in our sample, the "to others" and "from others" directional return connectedness plots in Figure 4.4 are smoother than the corresponding total directional volatility connectedness plot in Figure 4.5.

Second, the upward trend we observed in the total return connectedness plots carries over to the "to" and "from" directional return connectedness plots for each stock market (see Figure 4.4). While the upward trend in the "from" connectedness is stronger and more visible, the strength of the upward trend in the "to" connectedness varies across markets. In the case of volatility connectedness, however, it was not possible to discern an upward trend in the total directional plots (see Figure 4.5).

The upward trend in the "from" connectedness is a clear sign of increased interdependence/interconnectedness over time. While the "to" connectedness plot is expected to capture whether a market transmits a shock to another market when it happens, the "from" connectedness degree for a market shows whether shocks from other markets are transmitted to the market in question. As the stock markets become more interdependent/interconnected, we would expect them to transmit more of the shocks to other markets, hence the "from" connectedness tend to be higher over time. In contrast, for the "to" connectedness degree to be higher, there need to be shocks to returns as well as increased interdependence.

Third, the total directional return and volatility connectedness indices for the United States, the United Kingdom, Germany, France, and, to a certain degree, Brazil are higher than the corresponding measures for Japan, Australia, Hong Kong, China, and India throughout the sample period.

Return Connectedness

Let's now focus on each country's "to," "from," and "net" total directional return connectedness. Brazil's "to" and "from" connectedness measures trend strongly upward. While Brazil's "to" and "from" connectedness was less than 20% in 1994, by the end of 2010 these measures were above 80% and 60%, respectively. As a result, the

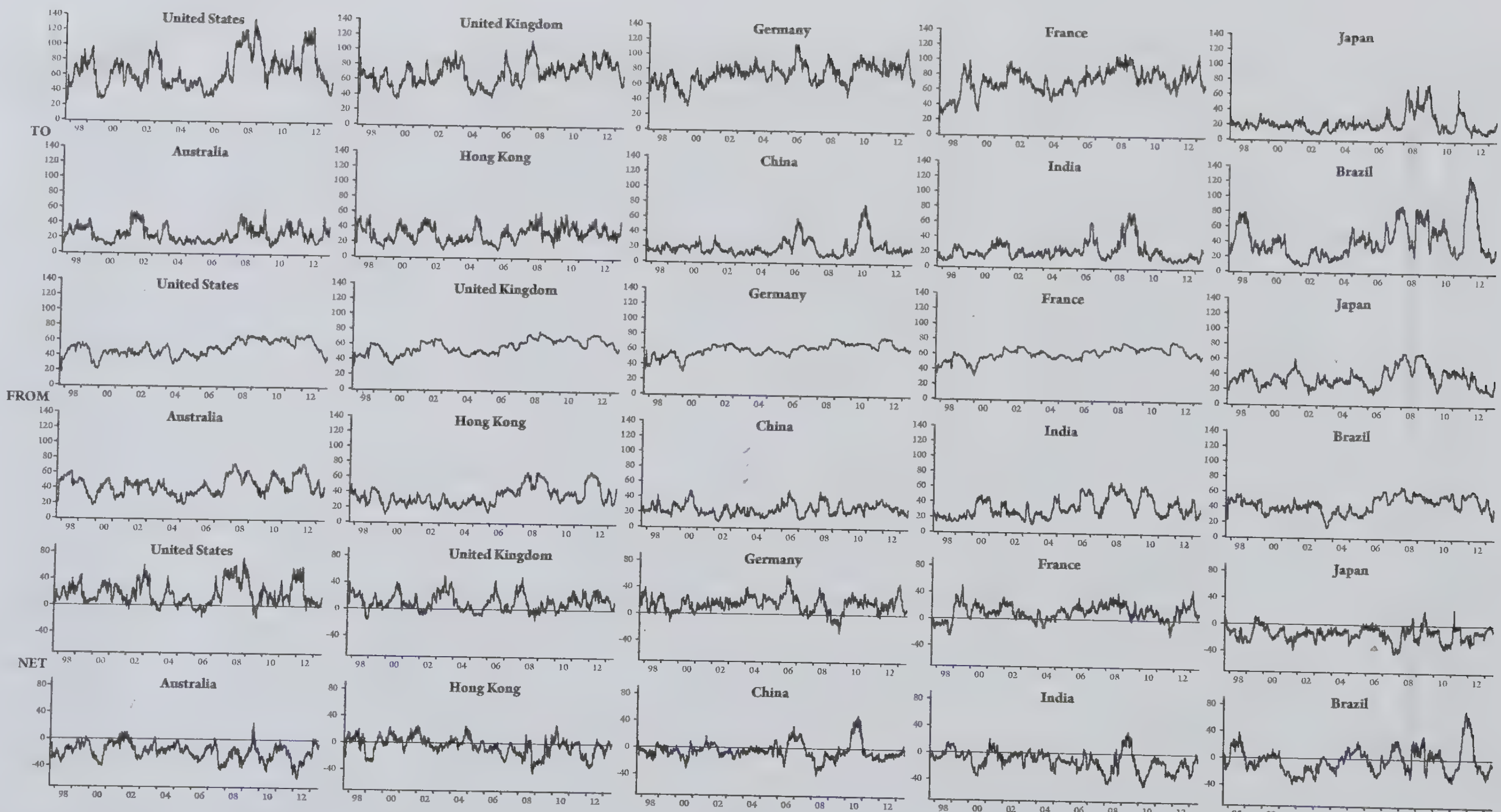


Figure 4.5 Total directional volatility connectedness—10 major stock markets (200-day window).

Brazilian stock market, which used to have close to zero net connectedness early in the sample, joined the four Western stock markets in the mid-2000s with positive net connectedness.

In the case of France, Germany, and the United Kingdom, the upward trend is more visible in the "to" connectedness, indicating that over time these markets have become more important for other markets to follow. As a result of the upward trend, their "to" connectedness levels reached the U.S. level by 2010. Because of the strong upward trend in their "to" connectedness, their net connectedness levels, which were close to zero in the 1990s, also moved up over time to move closer to the U.S. level.

Japan stands out among the developed stock markets. The upward trend is more pronounced in Japan's "from" connectedness rather than its "to" connectedness. Its "to" connectedness had a slight upward trend before the global crisis, but its "to" connectedness declined during the crisis. Over time, the French, German, and British stock markets have become more important, with positive connectedness measures. In the meantime, Japan solidified its follower status over time. Its net connectedness, which was close to zero in the mid-1990s, declined to –60%.

The U.S. stock market's "to" connectedness was less than 80% in 1994. Over time, its "to" connectedness increased slightly, with occasional drops and upward jumps. The upward trend in the U.S. stock market's "from" connectedness is much more significant, indicating that other markets have become more important for the U.S. stock markets over time. India's "from" connectedness also trended strongly upward, but the trend in its "to" connectedness is visible only after 2006. Despite an upward move in its "from" connectedness during the second half of the 2000s, China's stock markets continued to have very low "to" connectedness until 2010. Its "to" connectedness increased by more than 8% in 2010. This could be a sign that the Chinese stock market will follow China's real economy to become a more connected member of the global financial markets. However, it is too early to make this claim more assertively. Despite their higher degrees of "to" connectedness in the second half of the 2000s, both China and India have negative net connectedness, which indicates that stock market returns in these countries still follow their cousins in the United States, the United Kingdom, Germany, France, and Brazil.

Hong Kong and Australia's "to" and "from" connectedness measures also showed slightly upward trends, but these trends were not strong enough to move their negative "net" connectedness measures into positive territory. The only time Hong Kong played an important role was during the East Asian crisis, when, as a regional hub for the East Asian emerging market economies, it was able to transmit the shock from these countries to other parts of the world.

Volatility Connectedness

As we have discussed above, volatility connectedness measures do not follow an upward trend over time. Instead of trending upward, volatility connectedness measures increase significantly during times of significant uncertainty and financial crises and stay high as long as the data pertaining to the crisis are included in the sample windows.

The four Western stock markets tend to have higher "to," "from," and "net" volatility connectedness than the other six markets, especially during episodes of major financial crises. The United States is a net transmitter of volatility with a high degree of "net" volatility connectedness after the 1998 Russian crisis and the ensuing troubles of LTCM, following the burst of the tech bubble in 2000, after the 9/11 terrorist attacks in the United States, and after the WorldCom/MCI scandal in July 2002.

Following the first outbreak of the sub-prime crisis in February–March 2007, the "net" connectedness of the U.S. increased to 40% but declined immediately after. It jumped during the liquidity crisis of August 2007, to 60%, and did not come down until the second quarter of 2008. The "net" connectedness of the U.S. stock markets jumped again after the Lehman Brothers' bankruptcy in September 2008. It reached close to 70%, the maximum level of "net" connectedness observed in any stock market during the 1996–2010 period. The "net" volatility connectedness of the U.S. stock market came down in the first few months of 2009, moving to negative territory for a couple of months in the summer and fall of 2009. Again it climbed up at the end of 2009 when the first news about the Greek/euro debt crisis started to come out and stayed around 20% until the end of June 2010.

Apart from the American stock market, the British, German, and French stock markets also had significantly positive "net" connectedness on several occasions. For example, the British stock market's "net" connectedness reached 40% during the East Asian crisis, following the tech-bubble burst in 2000, following the Iraq War in 2003, after the Fed's decision to increase its policy interest rate in 2006, and during the liquidity crisis of 2007.

The German stock market's "net" connectedness index increased to 40% after the East Asian crisis of 1997. It increased to 30% after the Russian crisis of 1998. After fluctuating around 20% in 2001 through 2003, it increased to 40% in late 2003. It increased the most, close to 60%, immediately after the Fed's surprise policy rate decision in 2006. The "net" connectedness of the German stock market increased to 40% in early 2008, but moved to negative territory after the collapse of Lehman Brothers. During the initial phase of the Greek/euro debt crisis in late 2009, it increased again to 30% and fluctuated around 30% until the end of 2010. As the sovereign debt crisis spread to Ireland, Portugal, Spain, and Italy, the "net" connectedness of the German stock market stayed around 30% by the end of 2010.

The "net" connectedness of the French stock market increased to 40% after the Russian debt crisis. After a brief respite, it increased again to 20% in 2000 and to more than 20% following the 9/11 terrorist attacks in the United States. Its "net" connectedness stayed close to 20% following the Fed's 2006 decision to raise the policy interest rate, as well as during the liquidity crisis of 2007 and throughout 2008. Interestingly, its "net" connectedness during the Greek debt crisis is lower than that of the German stock market, but still positive.

As we have already noted, the "net" connectedness of the other six markets, for a large part of the sample, lies below zero, indicating that these markets were receiving volatility shocks transmitted by the four Western markets. In particular, Japan and Australia had negative "net" connectedness throughout the sample. Hong Kong and India also had negative "net" connectedness for the most part, but occasionally they had positive values of "net" connectedness.

China, India, and Brazil are also on the receiving end of volatility shocks. However, they occasionally generated significant "net" volatility connectedness to others. For example, China had approximately 10% "net" connectedness following the Fed's surprise interest rate hike in 2006. Its "net" connectedness reached close to 20% in the middle of 2010. This increase in connectedness resulted from the increased volatility and the more than 20% decline in Shanghai composite stock index in the first seven months of 2010, as the Chinese Central Bank tightened its grip on ever-expanding credit channels. Other than a 10% "net" connectedness in 2009, India did not have much influence on volatility in other markets. Brazil, on the other hand, had positive connectedness ranging around 10% in 1998, in 2005, in 2007, and in 2009.

Earlier in Chapter 3 we discussed why this was so. Let's repeat it here. The "to" connectedness measure shows that shocks are transmitted to others. However, the fact that a shock takes place in any stock market does not imply that all of the other markets will receive all of the transmitted shock. Rather, the transmitted shock as measured in the jump in the "to" connectedness will be distributed among the remaining nine markets depending on how connected these markets are with the market that was subject to the shock in the first place. As a result, the "from" connectedness plots are expected to be smoother compared to the "to" connectedness plots for each of the stock markets. Smoother dynamic "from" connectedness graphs are consistent with lower dispersion in the static "from" connectedness measures in Figure 4.2.

Discussing the "from" connectedness measures, we need to highlight the striking difference between the "from" connectedness plots of the four Western markets and of the six other markets included in our analysis. The "from" connectedness plots of the four Western markets are much smoother than those of the other markets. This difference means that when there is a volatility shock in one of the stock markets, the bulk of the shock is likely to be transmitted to the six other markets. This makes sense given the importance of the four Western stock markets that happen to be the most integrated, best capitalized, and most liquid. The "from" connectedness plots for other markets are less smooth compared to those of the four Western markets. Yet their "from" connectedness measures are much smoother compared to their "to" connectedness measures.

4.3.3 Pairwise Directional Connectedness

In the remainder of this chapter, we will discuss the pairwise directional connectedness of the major stock markets around the world. We present the rolling pairwise directional return and volatility connectedness plots in Figures 4.6 and 4.7. Each graph entails a 10×10 matrix of pairwise directional connectedness plots among each pair of stock markets. The diagonal connectedness plots range from 0% to 100%, whereas the off-diagonal plots range from 0% to 30%.

Return Connectedness

It is interesting that for all countries, "own" return connectedness measures (located in the diagonal of the overall graph matrix) decrease over time. The steady decline in the "own" connectedness of returns over time obviously goes together with the upward trend in the "from" connectedness of all stock markets (see "from" directional connectedness sub-plots in the last column of the matrix in Figure 4.6). Since we have already discussed it in detail above, we are not going to spend more time on the gradual increase in the directional return connectedness measures.

The only market with a different "own" connectedness in its returns plot is China. The "own" connectedness of the Chinese stock market stayed around 80% from 1991 to mid-2000s, with a very little downward move. The rather high degree of "own" connectedness over a decade indicates that the Chinese stock market was very little integrated with other major stock markets until the mid-2000s. Since the beginning of the global crisis in 2007, however, the "own" connectedness of the Chinese market moved down 40 percentage points. However, it is too soon to tell whether the Chinese stock market will become more connected with other stock markets over time.[6] India also had high "own" connectedness in the 1990s. However, unlike the Chinese stock market, it became more connected with other markets in the early 2000s. During the crisis, the connectedness of the Indian stock markets increased slightly, which was partially reversed in the second-half of 2010 and in 2011. A similar movement was observed in Japan's "own" connectedness plot as well.

[6] In our analysis we included the overall index for the Shanghai stock exchange, where an overwhelming majority of the stocks were not open to foreign ownership.

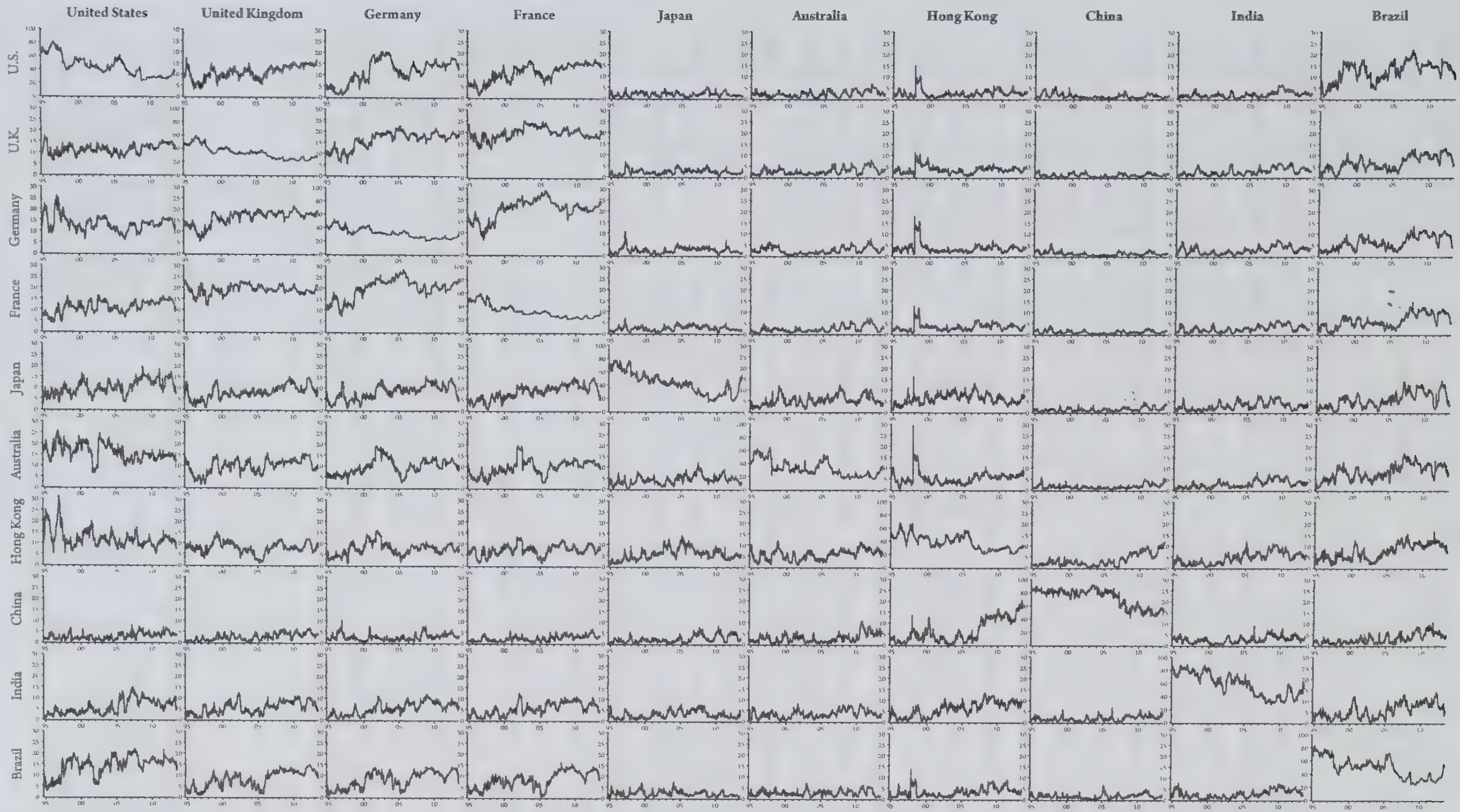


Figure 4.6 Pairwise directional return connectedness—10 major stock markets (200-day window).

Moving to the off-diagonal elements of the return connectedness graph matrix, we observe that pairwise directional connectedness in the first four columns (perhaps with the exception of the sub-plots in the eighth row, which belongs to China) are much higher than the other sub-plots. This means that higher pairwise directional connectedness involves one of the four Western developed stock markets (the United States, the United Kingdom, Germany, and France). As we have already seen in Figure 4.4, these are the markets that have the highest total directional connectedness. Therefore, it is not surprising that their pairwise directional connectedness is also high. What is interesting, however, is that their "to" connectedness to other markets (see columns 1 through 4 and rows 5 through 10) is also high. Perhaps the only market with which they had low "to" connectedness is the Chinese stock market. As we have already alluded to above, this is because, for most of the sample, China received very little pairwise directional connectedness from other markets.

One factor that helps to explain the rather high pairwise connectedness among the top four stock markets is the regional factor. They are all located in the North Atlantic region. The regional factor can be even more important in explaining the high connectedness among the three developed markets of the East, namely, Japan, Hong Kong, and Australia. In addition to having high pairwise directional connectedness among each other, these markets also have high "from" connectedness with the four Western developed stock markets as well as the Brazilian stock market. However, their pairwise "to" connectedness with the four Western markets and the emerging stock markets are very low. However, there are several exceptions to this generalization, Hong Kong had a very high "to" connectedness with all of the other markets during the East Asian crisis. Hong Kong also had high connectedness with India and China during the global financial crisis.

Finally, among the three emerging stock markets, Brazil is the only one that had strong "to" connectedness with other stock markets (except for China). Brazil also has strong "from" connectedness with the four Western developed stock markets, but not with the Eastern developed stock markets. As a result, we can conclude that the Brazilian stock market has high directional return connectedness with the major stock markets around the world.

Volatility Connectedness

There are a couple of important differences between the pairwise volatility and return connectedness plots in Figures 4.6 and 4.7. The most striking and important difference one can observe is the difference in their oscillations. We observe more oscillation in the pairwise volatility connectedness plots than in the pairwise return

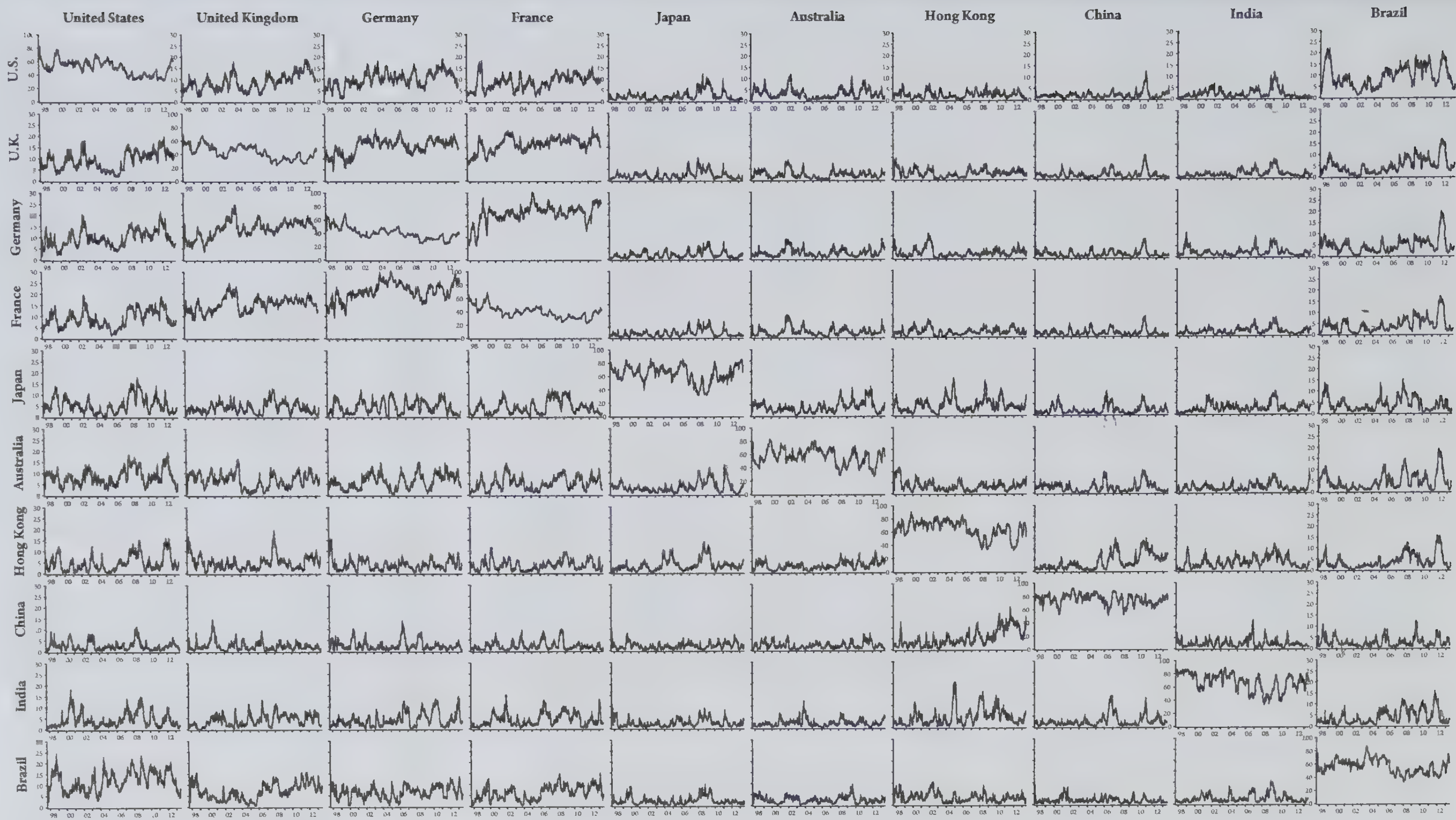


Figure 4.7 Pairwise directional volatility connectedness—10 major stock markets (200-day window).

connectedness plots. This is also true for all total "to" connectedness plots at the bottom row and most of the total "from" connectedness plots in the last column.

Some volatility connectedness plots have very few oscillations. Among the 100 connectedness plots in Figure 4.7, four of them stand out with their relatively smooth behavior over time. These are the "own" connectedness plots of the four Western developed stock markets. Even though the pairwise "from" connectedness with each of the other countries may be oscillating over time, when they are added up, their overall contribution to the forecast error variance of the volatility movements in the stock market in question is not oscillating as much. As a result, because the four Western developed stock markets are the best capitalized and most liquid markets, when there are volatility shocks in other markets, the resulting effect will not lead to significant changes in their "own" and "from" connectedness plots.

Similar to the case in returns, the pairwise "to" volatility connectedness of the four Western developed stock markets with other stock markets, again, with the exception of China, is high. Actually, their "to" pairwise connectedness with other markets is not always high. However, when there are volatility shocks in the four Western developed stock markets, these shocks lead to a substantial increase in the volatility connectedness to the other six markets. Once the data for the period are dropped from the rolling sample windows, the pairwise volatility connectedness declines sharply. This is actually the essence behind the oscillation.

The pairwise volatility connectedness among the three European stock markets (the United Kingdom, Germany, and France) is very high and tends to increase over time. Their pairwise volatility connectedness with the United States, on the other hand, is not as high and does not follow an upward trend. Here, again, the regional factor may be instrumental in generating these patterns.

4.A APPENDIX: STANDARD ERRORS AND ROBUSTNESS

As we did in Chapter 2, in this appendix we present two sets of information critical for the reliability of the results presented in the chapter. First, Tables 4.A.1 and 4.A.2 present the full-sample return and volatility connectedness tables along with the standard errors for total and pairwise connectedness measures obtained through the nonparametric bootstrap method.

As has been the case in Chapter 3, an overwhelming majority of return and volatility connectedness measures are statistically significant at the 1% or 5% level. The only exception is the Chinese stock market. China's pairwise return connectedness "to" the United States, the United Kingdom, Germany, France, and Brazil are not statistically different from zero. Similarly, China's pairwise volatility connectedness to the United

Table 4.A.1 Return Connectedness Table with Standard Errors, 10 Major Stock Markets

	USA	*UK*	*GER*	*FRA*	*JPN*	*AUS*	*HKG*	*CHN*	*IND*	*BRA*	*FROM*
USA	42.3**	13.4**	14.6**	13.6**	0.8**	1.5**	2.0**	0.0	1.3**	10.4**	57.7**
	(1.28)	(0.47)	(0.47)	(0.46)	(0.25)	(0.35)	(0.42)	(0.04)	(0.26)	(0.53)	(1.28)
UK	13.2**	32.9**	18.0**	21.9**	1.6**	2.2**	3.1**	0.1	1.7**	5.3**	67.1**
	(0.48)	(0.68)	(0.38)	(0.37)	(0.27)	(0.32)	(0.35)	(0.05)	(0.26)	(0.37)	(0.68)
GER	13.4**	18.4**	33.6**	22.5**	1.2**	1.8**	2.9**	0.1	1.3**	4.7**	66.4**
	(0.47)	(0.38)	(0.68)	(0.44)	(0.25)	(0.27)	(0.39)	(0.05)	(0.22)	(0.39)	(0.68)
FRA	12.8**	21.6**	21.7**	32.0**	1.3**	1.7**	2.5**	0.1	1.5**	4.9**	68.0**
	(0.44)	(0.32)	(0.38)	(0.58)	(0.23)	(0.27)	(0.30)	(0.05)	(0.22)	(0.36)	(0.58)
JPN**	11.7	8.8	8.2	8.7	45.3	5.2	5.4	0.3	2.1	4.5	54.7
	(0.61)	(0.46)	(0.48)	(0.47)	(1.63)	(0.59)	(0.59)	(0.11)	(0.32)	(0.42)	(1.63)
AUS**	16.4	11.3	9.4	10.3	3.7	32.9	5.8	0.4	2.5	7.3	67.1
	(0.60)	(0.48)	(0.47)	(0.46)	(0.50)	(1.37)	(0.53)	(0.14)	(0.32)	(0.48)	(1.37)

continued

Table 4.A.1 (continued)

	USA	*UK*	*GER*	*FRA*	*JPN*	*AUS*	*HKG*	*CHN*	*IND*	*BRA*	*FROM*
HKG**	10.8	8.5	6.9	7.0	4.9	7.1	43.2	1.6	4.0	6.0	56.8
	(0.62)	(0.49)	(0.52)	(0.46)	(0.62)	(0.65)	(1.51)	(0.28)	(0.46)	(0.51)	(1.51)
CHN	0.6**	0.7**	0.6**	0.6**	0.6**	1.1**	3.5**	90.6**	1.2**	0.4*	9.4**
	(0.22)	(0.23)	(0.21)	(0.21)	(0.22)	(0.36)	(0.59)	(1.49)	(0.28)	(0.19)	(1.49)
IND**	4.7	4.5	3.9	4.2	1.7	3.2	5.7	0.7	68.2	3.2	31.8
	(0.55)	(0.53)	(0.47)	(0.47)	(0.40)	(0.50)	(0.65)	(0.18)	(2.24)	(0.46)	(2.24)
BRA	14.1**	8.1**	7.1**	7.6**	0.9**	1.5**	2.2**	0.1	1.4**	57.0**	43.0**
	(0.60)	(0.50)	(0.55)	(0.48)	(0.27)	(0.35)	(0.46)	(0.09)	(0.29)	(1.91)	(1.91)
TO**	97.8	95.1	90.4	96.3	16.6	25.4	33.1	3.4	17.0	46.6	
	(2.89)	(2.08)	(2.18)	(1.93)	(2.21)	(2.10)	(2.51)	(0.58)	(1.83)	(2.60)	
NET	40.1**	28.0**	24.0**	28.3**	–38.0**	–41.7**	–23.7**	–5.9**	–14.8**	3.7*	**52.2****
	(2.33)	(1.65)	(1.72)	(1.60)	(2.19)	(2.14)	(1.95)	(1.12)	(1.14)	(1.47)	(1.00)

Notes: The sample is taken from January 3, 1994 through June 28, 2013. Nonparametically bootstrapped standard errors (5000 drawings) are presented in parentheses. ** and * indicate statistical significance at the 1% and 5% levels. ** next to the row heading indicates that *all entries* of the row are significantly different from zero at the 1% level.

Table 4.A.2 Volatility Connectedness Table with Standard Errors, 10 Major Stock Markets

	USA	*UK*	*GER*	*FRA*	*JPN*	*AUS*	*HKG*	*CHN*	*IND*	*BRA*	*FROM*
USA	46.9**	12.7**	13.2**	13.0**	1.8**	2.5**	3.0**	0.1	0.6*	6.3**	53.1**
	(1.59)	(0.88)	(0.92)	(0.89)	(0.50)	(0.58)	(0.67)	(0.12)	(0.33)	(0.73)	(1.59)
UK	12.5**	40.1**	19.4**	18.0**	0.9**	2.9**	3.0**	0.1	0.4	2.8**	59.9**
	(0.91)	(1.16)	(0.87)	(0.79)	(0.34)	(0.60)	(0.64)	(0.14)	(0.23)	(0.54)	(1.16)
GER	11.2**	16.3**	44.5**	21.5**	0.9*	0.9*	1.9**	0.1	0.0	2.7**	55.5**
	(0.93)	(0.87)	(1.28)	(0.85)	(0.37)	(0.37)	(0.54)	(0.13)	(0.07)	(0.57)	(1.28)
FRA	12.9**	18.0**	23.7**	38.3**	0.9**	1.8**	2.2**	0.0	0.1	2.0**	61.7**
	(0.89)	(0.80)	(0.84)	(0.98)	(0.34)	(0.47)	(0.54)	(0.07)	(0.11)	(0.45)	(0.98)
JPN	8.1**	4.1**	4.5**	5.0**	65.2**	1.9**	5.8**	0.2	1.3**	3.9**	34.8**
	(1.02)	(0.76)	(0.85)	(0.84)	(2.52)	(0.52)	(0.97)	(0.13)	(0.49)	(0.85)	(2.52)
AUS	10.5**	10.8**	4.2**	5.7**	1.5**	56.4**	5.0**	1.9**	1.1**	2.9**	43.6**
	(1.07)	(1.05)	(0.78)	(0.86)	(0.43)	(2.44)	(0.91)	(0.62)	(0.46)	(0.70)	(2.44)
HKG	7.2**	6.8**	2.8**	3.2**	3.0**	2.9**	64.8**	1.1**	4.1**	4.2**	35.2**
	(1.05)	(1.00)	(0.74)	(0.74)	(0.72)	(0.73)	(2.62)	(0.34)	(0.90)	(0.92)	(2.62)

continued

Table 4.A.2 (continued)

	USA	*UK*	*GER*	*FRA*	*JPN*	*AUS*	*HKG*	*CHN*	*IND*	*BRA*	*FROM*
CHN	0.5	0.3	0.1	0.1	0.4	2.0**	1.7**	93.6**	0.9	0.5	6.4**
	(0.37)	(0.28)	(0.20)	(0.16)	(0.21)	(0.73)	(0.56)	(1.31)	(0.52)	(0.35)	(1.31)
IND	4.2**	2.4**	0.7	0.7	1.6**	1.0*	7.9**	0.6	77.6**	3.2**	22.4**
	(0.94)	(0.71)	(0.41)	(0.39)	(0.61)	(0.47)	(1.27)	(0.41)	(2.61)	(0.88)	(2.61)
BRA	11.6**	6.0**	5.8**	4.0**	1.7**	1.2**	5.5**	0.0	1.2**	63.0**	37.0**
	(0.99)	(0.81)	(0.86)	(0.69)	(0.56)	(0.45)	(0.96)	(0.09)	(0.48)	(2.23)	(2.23)
TO	78.6**	77.3**	74.3**	71.1**	12.7**	17.0**	35.9**	4.2**	9.7**	28.6**	
	(5.41)	(4.84)	(4.37)	(4.22)	(2.82)	(3.29)	(4.68)	(1.16)	(2.41)	(4.12)	
NET	25.5**	17.5**	18.8**	9.4*	–22.1**	–26.6**	0.7	–2.2	–12.6**	–8.4	**41.0****
	(5.81)	(5.12)	(4.67)	(4.47)	(3.63)	(4.05)	(5.40)	(1.55)	(3.51)	(4.42)	(1.17)

Notes: The sample is taken from December 4, 1996 through June 28, 2013. Nonparametically bootstrapped standard errors (5000 drawings) are presented in parentheses. ** and * indicate statistical significance at the 1% and 5% levels.

States, the United Kingdom, Germany, France, Japan, India, and Brazil are not statistically different from zero. This result shows that Chinese stock market is not strongly connected to other major stock markets around the world.

All total "from," "to," and "net" return connectedness measures are also strongly significant. Among the total directional volatility connectedness measures, the "net" total volatility connectedness measures for Hong Kong, China, and Brazil are not statistically significantly different from zero.

Figures 4.A.1 and 4.A.2 present sensitivity of the total return and volatility connectedness plots to variation in forecast horizon, H, and the VAR model order, p.

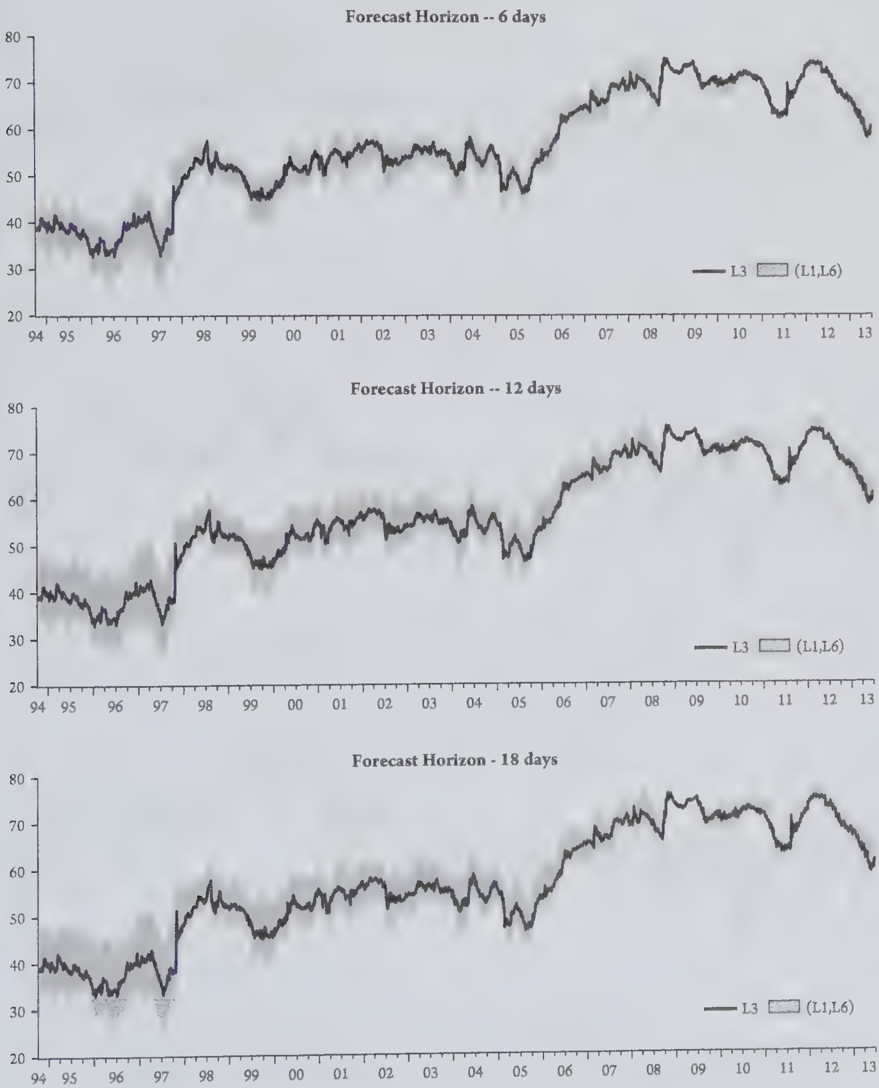


Figure 4.A.1 Robustness to forecast horizon and lag choice, total stock return connectedness. See the caption in Figure 2.A.1.

Figure 4.A.1 clearly shows that the total return connectedness plot is very robust to changes in both parameters. There is no significant change in the time-series behavior of the gray-shaded band and the black line as we change the forecast horizon from 6 to 12 days and 18 days. Furthermore, the gray-shaded band of VAR order 1 and 6 is quite narrow and got narrower during the global financial crisis.

A similar observation can be made for the volatility connectedness plots in Figure 4.A.2. The volatility connectedness plot for VAR(3) varies very little with the

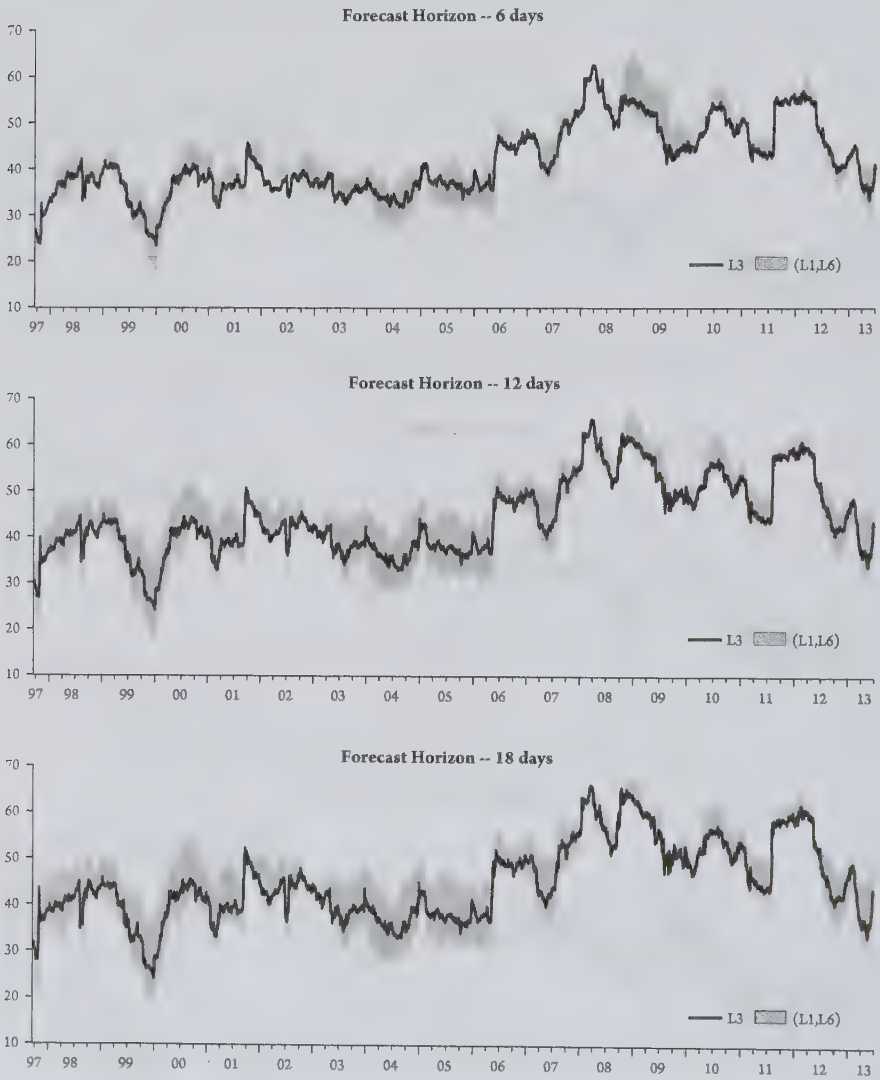


Figure 4.A.2 Robustness to forecast horizon and lag choice, total stock return volatility connectedness.
See the caption in Figure 2.A.1.

change in the forecast horizon. A wider gray-shaded band compared to the one we obtained in the case of return connectedness indicates that the volatility connectedness plot is more sensitive to the variations in the VAR model order, *p*. Despite the wider margin, volatility connectedness plots for VAR mode order 1, 3, and 6 moves up and down in tandem.

5

SOVEREIGN BOND MARKETS

The eurozone debt crisis and its impact on global financial markets have shown that the global bond markets can be highly connected during times of crises. That is why in this chapter we focus on the connectedness of the interest rates on long-term government bonds and their volatilities across countries.

Bond markets are as crucial as the stock markets. In industrial countries, they are the major source of financing for local, state, and federal governments as well as corporations. Once a corporation offers its stock to be sold to the public, the stock market ceases to be a major source of financing. The bond market, on the other hand, is a perpetual source of finance through which corporations and states can borrow at lower rates compared to the cost of borrowing from commercial banks.

As a financial asset, bonds have several characteristics that differentiate them from stocks. A stock is a financial asset that never matures. Its value can increase in multiples or go down all the way to zero. The volatilities of individual stock and stock market returns reflect these characteristics. Bonds, especially the so-called "riskless" sovereign bonds, have a different distribution of returns. Unlike stocks and other major financial assets such as commodities and foreign currency, bonds mature at a future point in time. Since bonds have a par value at maturity, their value cannot go to zero unless the debtor defaults, nor can their value increase in multiples.

Bond market volatility is also quite different from stock market volatility. We should care about the level of volatility in a bond market because the greater the bond volatility, the greater the risk of lending and the more compensation lenders must demand in the form of higher interest rates. If one thinks that lower long-term rates are good for the economy, then lower volatility in the long-term bond markets is even better.

In this chapter, we focus on sovereign bond markets in industrial countries. We put together a data set for 12 countries: the United States, the United Kingdom, Germany, Japan, France, Canada, Australia, Italy, Spain, Portugal, Ireland, and Greece. For 11 countries (excluding Greece) the interest rate data start in April 1991. Greek interest rate data, however, start in March 1997. The Irish bond yield index ends in October 2011, earlier than the others. For that reason, we include only 10 countries in our analysis. For all 12 countries, the daily minimum and maximum interest rates needed to calculate the range estimate of volatility have been available since January 1999. However, in the case of Ireland and Portugal, the data on daily minimum and maximum interest rates are not available on a continuous basis. As a result, in our analysis of the volatility connectedness from 1999 to 2012 we include 10 countries only. While we include Portugal in the daily returns analysis along with nine others, in the volatility connectedness analysis we include Greece, instead of Portugal.

There is a voluminous literature focusing on the dynamics of long-term interest rates and their volatility in industrial countries. The literature on return and/or volatility spillovers across bond markets, however, is not as extensive as the literature on stock markets. We hope to contribute to this literature. However, before going ahead with the analysis, we first provide a brief review of the literature on bond market return and volatility spillovers.

With the integration of the financial markets, one would expect the co-movement of long-term interest rates to increase. Christiansen and Piggot (1997), in an earlier contribution to the literature, study the co-movement of long-term interest rates. Applying various empirical tools to monthly data on long-term interest rates for the United States, Europe, and Japan, they show that globalization led to an increase in the co-movement of long-term interest rates. Their research was initially motivated by the co-movement of long-term interest rates between 1993 and 1995 in the three countries, despite the fact that these three countries/regions were at different stages of their respective business cycles. In particular, the long-term interest rates in Europe and Japan increased in 1994 in the wake of monetary tightening by the Fed.

In another important contribution, using a bivariate GARCH framework, Hunter and Simon (2005) find that return and volatility spillovers between the major international bond markets are much weaker than those between equity markets. Their results also indicate that the correlations between bond market returns are time varying and are driven by the changes in macroeconomic environment and market conditions. More importantly, Hunter and Simon (2005) conclude that the benefits of diversification across major sovereign bond markets did not decrease during periods of high market volatility or following negative U.S. and foreign bond returns.

During periods of rising inflation in different countries, international bond prices could move down together, leading to higher correlations in daily bond returns, a phenomenon that is more frequently observed in stock markets. During these periods, investment in international bonds will not contribute to portfolio diversification and hence these bonds would lose their attractiveness for portfolio managers. The Federal Reserve's monetary policy tightening in 1994 led to a situation similar to the one described here. At the time, Fed's monetary policy tightening led to a sharp increase in long-term interest rates not only in the United States but also in Japan and the European countries, even though the future economic outlook in the latter was quite bleak (for more information, see Christiansen and Piggot (1997)). We will discuss the 1994 episode in more detail when we analyze the total return connectedness.

Dungey et al. (2006) studied contagion in international bond markets during the 1998 Russian and Long-Term Capital Management (LTCM) crises. They built a latent-factor model of long-term bond yield volatilities spanning bond markets across Asia, Europe, and the Americas. Their findings suggest that while the bond yield volatility of some countries were directly influenced by the Russian debt crisis, others were influenced more by the volatility in the U.S. financial markets once the LTCM hedge fund ran into difficulty in the second half of 1998.

Following the outbreak of the Greek sovereign debt crisis, there has been increased interest on contagion across sovereign debt markets in the Economic and Monetary Union (EMU) countries. Ehrmann et al. (2011) showed that the EMU led to substantial convergence in the euro-area sovereign bond markets in terms of interest rate levels, unconditional daily fluctuations, and conditional responses to major macroeconomic announcements. This finding has two implications for connectedness analysis in bond markets. First, the connectedness across European countries is likely to increase over time following the EMU. After a while, it might be quite legitimate to use bond yield for one or two countries (Germany and France, for example, will be sufficient to represent the European bond markets) in an analysis of the global bond markets. In another study, using a simultaneous equation model of contagion, Metiu (2011) showed that a large number of EMU member countries had been vulnerable to the contagion of sovereign debt market stress, originated from Greece, Ireland, Portugal, and Spain.

5.1 BOND MARKET DATA

As we have already discussed in the introduction, this chapter focuses on the return and volatility connectedness across major bond markets. There are 10 countries in the sample for both daily bond returns and return volatility. Nine of the countries are included in both analyses. We include Portugal and Greece as the tenth country in the return and volatility connectedness analyses, respectively.

We have daily open, close, high, and low values for the 10-year government bond yields, but not for the bond prices. Assuming that the average coupon rate of the bonds that make up the index does not change from one day to the other, for market i on day t we can write the relationship between the yield $(r_{i,t})$ and price $(P_{i,t})$ indices as $P_{i,t} = \frac{100}{(1+r_{i,t})^N}$. Having obtained the daily bond prices in this fashion, we measure daily bond returns from the 10-year government bond prices as $\rho_{it} = \ln(P_{i,t}/P_{i,t-1}) * 100$.

We plot the daily yields for 10-year government bonds in Figure 5.1. As can be seen in Figure 5.1, in all 10 bond markets, daily bond yields follow a downward trend, with some significant intermissions, from 1991 until the mid-2000s. While some markets (such as the United States, the United Kingdom, Germany, France, Japan, Canada, and Australia) continued the downward trend in yields until the end of our sample, the crisis hit countries (such as Italy, Spain, and Portugal) experienced a reversal in the daily bond yields since the beginning of the sovereign debt crisis in some of the EU countries.

We measure daily volatility with the range estimate. In order to simplify the volatility calculations, our range volatility relies on the log of the ratio of the maximum and minimum daily yields only. In other words, we do not make use of the opening and closing values for yields. Instead, following Parkinson (1980), we estimate daily variance using natural logarithms of daily high and low prices as in equation (2.1).

Due to the lack of data on daily high and low bond prices in some bond markets prior to 1999, our analysis of volatility connectedness is confined to the 1999–2013 period. Even though the Greek and Spanish sovereign bond markets are relatively small in terms of size and liquidity, we include them in the analysis to gauge whether the volatility connectedness of each of these markets has followed different patterns since the beginning of the eurozone debt crisis. We are not able to include Ireland and Portugal in the full sample analysis, as the daily minimum and maximum values of interest rates for these countries are missing for certain periods prior to 2007.[1]

[1] Given the fact that these countries are critical to develop a better understanding of the eurozone debt crisis, we also analyzed the volatility connectedness after 2007 including the two countries and compared these with the results for the 10-country group. We do not report those results, as the obtained total and pairwise connectedness measures do not lead to different qualitative results than reported in this chapter.

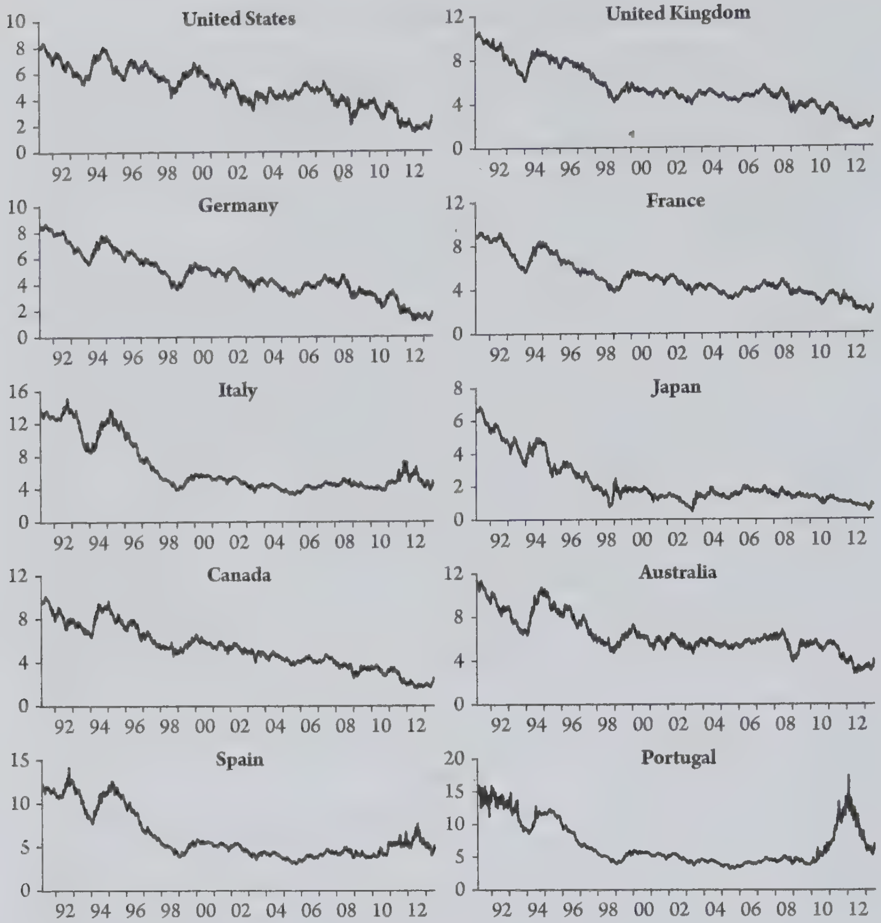


Figure 5.1 Daily 10-year government bond yields (% per annum).

Tables 5.1 and 5.2 present the descriptive statistics of the annualized 10-year government bond daily returns and daily return volatilities for 10 countries. Since we use the log range volatility series in our volatility connectedness analysis, in Table 5.2 we tabulate the skewness and the kurtosis for the log range volatility, whereas the descriptive statistics (mean, median, maximum, minimum, and standard deviation) for the range volatility are presented in levels.

Annualized mean daily returns are all positive. Median daily returns for France, Japan, Australia, and Portugal are all equal to zero, while they are positive for other countries in the sample. Portugal has the most volatile daily returns followed by Australia, Italy, Spain, and the United States. Portugal has both the highest and the lowest daily returns on bonds, followed by Spain and Italy. Daily returns are mostly skewed to the right (only three are skewed to the left), and they are all leptokurtic.

Table 5.1 Descriptive Statistics—Annualized 10-year Government Bond Returns (April 1991–June 2013)

	United States	*United Kingdom*	*Germany*	*France*	*Italy*
Mean	3.0	4.4	3.9	3.9	5.4
Median	6.7	3.5	3.6	0.0	3.5
Maximum	1,682.1	1,767.1	920.6	1,011.1	2,756.0
Minimum	−1,154.4	−1,150.5	−819.2	−949.8	−2,072.5
Std. Dev.[a]	215.5	193.4	155.0	163.1	251.2
Skewness	−0.097	−0.053	−0.217	−0.164	0.076
Kurtosis	5.068	6.767	4.943	5.187	13.062
Jarque–Bera	1,034.0	3,404.5	950.0	1,172.7	24,268.9
	Japan	*Canada*	*Australia*	*Spain*	*Portugal*
Mean	3.6	4.0	4.3	4.4	4.7
Median	0.0	3.5	0.0	3.5	0.0
Maximum	1,575.3	941.2	1,532.1	3,055.6	8,690.9
Minimum	−1,350.6	−1,313.3	−1,608.5	−1,485.2	−6,819.6
Std. Dev.	132.7	189.5	253.5	245.2	680.3
Skewness	−0.37	−0.18	−0.25	0.72	0.80
Kurtosis	13.70	5.20	5.93	17.01	41.90
Jarque–Bera	27,572.8	1,186.7	2,116.3	47,543.1	363,353.3

[a]Std. Dev., standard deviation.

What we observed in the case of global stock markets is also true for the global bond markets. The mean volatility is higher than the median volatility. This is an indication that the global bond market volatility is skewed to the right due to the recent global financial crisis. In the case of Greece, the mean bond return volatility is almost three times the median volatility. The skewness and kurtosis measures of the log range volatility are further away from the normal distribution and the Jarque–Bera test rejects the normality of the log range volatility at the 5% significance level over the full sample for all countries.

If we look at the descriptive statistics of volatility in each of the sovereign bond markets, the Japanese bond market stands out. Japanese government bonds had the lowest mean, median, and standard deviation of volatility over the period from 1999 to June 2013. The 10-year U.S. government bonds, on the other hand, had the highest median volatility and the second highest mean volatility after the Greek government bonds.

Table 5.2 Descriptive Statistics—Annualized 10-Year Government Bond Yield Volatility (January 1999–June 2013)

	United States	*United Kingdom*	*Germany*	*France*	*Italy*
Mean	9.96	7.42	7.09	7.08	7.64
Median	8.84	6.63	6.34	6.30	5.98
Maximum	61.7	46.9	32.5	37.8	78.4
Minimum	0.033	0.109	0.113	0.888	0.331
Std. Dev.[a]	5.15	3.71	3.47	3.63	6.22
Skewness (log)	−1.57	−1.08	−0.17	0.11	0.41
Kurtosis (log)	13.92	10.33	4.68	3.17	3.91
Jarque-Bera (log)	19816.1	8965.3	450.8	11.4	232.7
	Japan	*Canada*	*Australia*	*Spain*	*Greece*
Mean	4.13	6.77	7.49	7.96	18.08
Median	3.40	6.06	6.24	6.27	6.09
Maximum	39.5	30.1	51.3	71.1	644.6
Minimum	0.113	0.109	0.216	0.442	0.108
Std. Dev.	2.83	3.58	4.80	6.25	38.43
Skewness (log)	−0.76	−1.40	−0.33	0.42	0.72
Kurtosis (log)	6.47	10.08	4.91	3.63	4.15
Jarque-Bera (log)	2206.3	8895.1	629.3	168.1	519.1

[a]Std. Dev., standard deviation.

5.2 FULL-SAMPLE RETURN AND VOLATILITY CONNECTEDNESS

Tables 5.3 and 5.4 present the bond market return and volatility connectedness measures for the full sample, as well as their nonparametrically bootstrapped standard errors. As can be seen in both tables, an overwhelming majority of the pairwise and total directional connectedness measures are statistically significant at the 1% level.

The mean return connectedness, 48.2%, is lower than the mean volatility connectedness, 53.7%, among the major 10-year government bond markets. The mean return connectedness among the major 10-year government bond markets is also lower than the mean return connectedness among the major stock markets, 52.2%, we obtained in Chapter 4. However, the mean volatility connectedness among the major bond markets around the world, 53.7%, tends to be significantly higher than the corresponding volatility connectedness, (41%) among the stock markets. This could be due to

Table 5.3 Return Connectedness Table, 10-Year Sovereign Bond Markets

	USA	*UK*	*GER*	*FRA*	*ITA*	*JPN*	*CAN*	*AUS*	*SPA*	*PRT*	*FROM*
USA	42.9	8.6	11.3	7.9	0.0	0.2	25.3	2.0	1.6	0.2	57.1
UK	9.0	38.8	20.6	16.6	0.2	0.2	8.3	0.9	5.2	0.3	61.2
GER	10.3	18.2	34.2	22.1	0.2	0.3	8.6	1.1	4.8	0.3	65.8
FRA	7.4	15.0	22.6	35.0	1.9	0.3	6.6	1.0	9.8	0.4	65.0
ITA	5.3	6.2	6.7	10.2	48.4	0.2	4.6	0.7	17.1	0.6	51.6
JPN	4.2	1.7	2.8	1.9	0.2	85.5	2.4	0.9	0.3	0.2	14.5
CAN	25.7	8.7	10.1	7.5	0.1	0.2	43.6	2.1	1.8	0.2	56.4
AUS	17.3	7.0	8.5	5.7	0.5	0.4	14.8	44.0	1.5	0.2	56.0
SPA	2.7	7.0	7.3	14.7	10.3	0.1	2.6	0.6	53.3	1.5	46.7
PRT	0.5	0.6	0.7	1.1	0.9	0.1	0.5	0.3	2.5	92.8	7.2
TO	82.4	73.1	90.5	87.6	14.2	2.0	73.7	9.5	44.6	4.0	
NET	25.3	11.9	24.7	22.6	−37.4	−12.6	17.3	−46.5	−2.1	−3.2	48.2

Notes: The sample is taken from April 4, 1991 through June 28, 2013. All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in this chapter's appendix, in Table 5.A.1.

Table 5.4 Volatility Connectedness Table, 10-Year Sovereign Bond Markets

	USA	*UK*	*GER*	*FRA*	*ITA*	*JPN*	*CAN*	*AUS*	*SPA*	*GRC*	*FROM*
USA	45.4	5.7	10.3	8.8	6.0	0.2	14.3	1.8	5.4	2.2	54.6
UK	5.1	38.1	14.4	12.3	8.9	0.3	4.2	1.8	9.9	5.0	61.9
GER	5.6	9.2	27.2	19.9	13.5	0.1	4.0	0.7	13.9	6.0	72.8
FRA	5.2	8.2	20.4	28.4	14.3	0.1	3.8	0.8	13.8	5.0	71.6
ITA	3.3	5.3	13.3	13.7	30.9	0.2	2.6	0.2	19.1	11.5	69.1
JPN	1.5	0.9	0.4	0.4	1.2	89.2	0.4	1.0	0.7	4.5	10.8
CAN	16.7	5.4	7.8	7.2	5.1	0.2	50.1	0.9	4.8	1.9	50.0
AUS	6.3	4.3	4.4	4.0	2.5	0.5	2.8	71.0	3.3	1.1	29.0
SPA	3.1	6.2	14.2	13.9	19.8	0.2	2.5	0.5	29.4	10.3	70.6
GRC	1.3	3.5	6.5	5.7	15.1	1.2	1.0	0.1	12.2	53.5	46.6
TO	48.1	48.7	91.5	86.0	86.2	3.0	35.6	7.6	83.0	47.4	
NET	−6.5	−13.2	18.7	14.4	17.1	−7.9	−14.4	−21.4	12.4	0.8	53.7

Notes: The sample is January 4, 1999 through June 28, 2013. All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in this chapter's appendix, in Table 5.A.2.

(a) the differences in the composition of stock and bond markets we included in the analysis and (b) the time periods covered.

German and French bond markets are the two most-connected markets in terms of returns and volatility. In the case of returns, with a "to" connectedness of 90.5%, the German bond market ranks at the top, closely followed by the French (87.6%). The two markets also have significantly higher trading volume compared to other Euro-zone bond markets. The American (82.4%), Canadian (73.7%), and British (73.1%) bond markets follow the French and German markets in terms of the "to" connectedness in returns. In the case of "from" connectedness in returns, German (65.8%) and French (65.0%) bond markets are followed by the British (61.2%) and U.S. (57.1%) bonds markets.

With a mean "to" connectedness of 91.5%, the German government bond market turns out to be the most connected in volatility, followed by the Italian (86.2%), French (86%), and Spanish (83%) bond markets. The "from" connectedness of the German bond market (72.8%) in volatility is the highest, followed by the French (71.6%) bond market. In terms of the "from" connectedness, the Spanish (70.6%), Italian(69.1%), and British (61.9%) bond markets follow the German and French markets.

The mean "net" connectedness measures in both bond returns and volatility vary substantially across countries. The "net" connectedness in returns varies from the lowest, –46.7%, for Australia, to the highest, 25.3%, for the United States. In between, the Italian, UK, French, and German bond markets have "net" return connectedness of –37.4%, 11.9%, 22.6%, and 24.7%, respectively. The range of the "net" volatility connectedness, on the other hand, is smaller, ranging from –21.4% for Australia to 18.7% for Germany. Japan and Portugal are the least-connected bond markets in returns, whereas Japan is the least-connected market in volatility (in terms of "to," "from," and "net" connectedness). Even though it has the fourth largest trading volume, the Japanese bond market is the market with the lowest "to" connectedness in return and volatility connectedness. Return and volatility shocks in the Japanese bond market have no effect on other bond markets.

Having a closer look into the pairwise connectedness measures, we observe that the European bond markets, especially the German, French, and British markets, stand out: They are tightly connected with each other in returns and volatility. The pairwise return and volatility connectedness measures of the three markets with each other range between 8.2% and 22.6%. In addition to these three, the Italian bond market has high (between 8.9% and 14.3%) pairwise volatility connectedness, especially with the German and French markets. Its pairwise "to" connectedness measures in returns with the three major European bond markets are less than 2% (only the one with the French market is statistically significant), while its pairwise "from" connectedness degrees in returns with these markets range between 6.2% and 10.2% (all statistically significant). The high pairwise return and volatility connectedness among the European bond markets can be due to the fact that, since the introduction of the euro in 1999, bonds in these countries have all been denominated in euros.

Despite the fact that the United Kingdom is not a member of the European Monetary Union (EMU), its bond market is tightly connected with the major continental bond markets. Its pairwise "to" and "from" return connectedness degrees with these markets reach as high as 20%. Unlike these markets, however, the U.K. bond market's "net" volatility connectedness is negative, –13.2%. The British bond market has negative pairwise "net" volatility connectedness with each of the three major continental bond markets (–5.2% with Germany, –4.1% with France and –3.6% with Italy).

Finally, let us have a brief look into the connectedness of the bond markets in the remaining three EU member countries included in our analysis. Spain has high "to" and "from" volatility connectedness with other European countries over the full sample. The Portuguese and Greek bond markets, on the other hand, are, the least-connected in returns and volatility, respectively. Even though the Greek debt crisis wrought havoc in the European financial markets from 2010 through 2012, the evidence for the connectedness of the Greek volatility shocks cannot be found when one relies on the full-sample analysis.

So far, we have not provided a detailed discussion of the differences in return and volatility connectedness across bond markets. There can be many factors and events that took place in the span of more than a decade that had the potential to affect the connectedness of each market. Instead, as we usually do, we defer the detailed analysis of directional connectedness to the dynamic rolling-windows analysis, which we turn to next.

5.3 DYNAMICS OF RETURN CONNECTEDNESS

We present the total return connectedness index in Figure 5.2. In 1992 the return connectedness index narrowly fluctuated around 38%. During the ERM crisis in September 1992, the return connectedness across major sovereign bond markets increased only slightly. During the week in which the British pound and the Italian lira left the ERM and Spain's peseta was devalued, the index increased from 39% on September 9 to 41% on September 14, 1992. The impact of the ERM crisis on bond markets did not last long, as reflected in the drop in the index immediately after the pound and the lira left the ERM and the peseta was devalued. The index continued its downward trend until mid-1993, hitting as low as 32% as the observations for September 1992 were dropped out of the sample window.

The index started to increase immediately after it hit the bottom in the middle of 1993. First gradually, then abruptly, the index moved up, to reach 40% at the end of

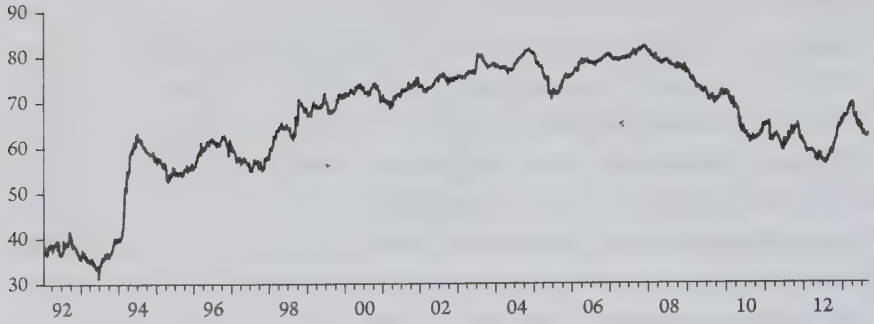


Figure 5.2 Total 10-year sovereign bond return connectedness (200-day window).

November 1993. After a short lull, the index experienced a very drastic increase from 41% to 63% in the five months from February 1, 1994. This was the most dramatic increase the index experienced for the whole period of analysis.

What happened over the course of five months from February 1 to July 1, 1994 that caused such a drastic increase in total return connectedness? The most critical factor at the time was the shift in the Federal Reserve's monetary policy stance. In its three consecutive meetings (February 4, March 22, and April 18), the FOMC increased the fed funds target rate by 25 basis points, followed by another 50 basis point increase on May 17. As a result, the fed funds target rate increased from 3% to 4.5% in less than four months. However, there was no such tightening in other major industrial countries. The central banks of the United Kingdom, Japan, Germany, and France actually lowered their policy rates during those four months. Hence, fear of inflation could not be so strongly felt in all major countries so as to cause the sudden increase in long-term rates across countries.

The sudden increase in the fed funds target rate actually helped burst a bubble in the major bond markets. The bubble in the market was a result of the "carry trade" strategy, whereby long-term bond purchases were financed by overnight borrowing in the United States at a low cost around 3%. As long as the short-term rates stayed low, investors traded confidently in long-term bonds, pocketing the spread between the long-term interests and the cost of carry. They relied on the same strategy and purchased government bonds in the United Kingdom, Germany, Canada, France, and other industrial countries where the long-term rates were above 5.5% at the beginning of 1994. However, once the Fed increased the policy rate by a quarter of a percent in February, it was sufficient to create panic among the leveraged speculators around the world, which led to an unwinding of carry trades and global sell-offs. As a result, the interest rates on 10-year U.S. government bonds increased by 141 basis points from 5.41% at the beginning of 1994 to 7.32% on July 1, 1994. The rise in long-term interest rates in other countries also increased, ranging from 101 basis points in Japan to 298 basis points in Australia (see Figure 5.1). As a result, the year 1994 has been described as one of the worst years in the history of the modern global bond markets.

Analyzing the directional connectedness plots (see Figure 5.3), it becomes evident that the "net" connectedness of the U.S., British, German, and French bond markets increased substantially during this episode to reach close to 30% by mid-1994. While the increases in the "to" and "net" connectedness of the U.S. lasted briefly, the corresponding upward moves in the "to" and "net" connectedness of the United Kingdom, Germany, and France were sustained and they were more sizable compared to those of the United States. Over this period, the pairwise "to" connectedness of the U.S. bond market to Australia increased most significantly (from 5% to 20%). Its "to" connectedness to other bond markets either increased by only 5 percentage points or did not increase at all. On the other hand, the pairwise connectedness of the U.K. bond market to all other markets, except for Japan, increased considerably (see Figure 5.4). Hence, our results support the view that the Fed's decision to tighten monetary policy led to a sell-off in major bond markets, which then led to a substantial increase in return connectedness mostly from the British, German, French, and American bond markets to others.[2]

From the end of 1994 to the end of 1998, the total return connectedness index experienced downward and upward movements between 53% and 63%, each of which lasted about a year. Over this period, the "to" and "net" connectedness of the American and British bond returns stayed high but also fluctuated, whereas the corresponding variables for the German bond market stayed high, above 25%, and the ones for the French bond market declined significantly by 1996 before increasing again to reach its 1994 levels by 1998.

There were several factors that contributed to the upward movement in 1998. First, it was a period of convergence in long-term bond yields of the eurozone member countries. Over the course of 1995 through 1997, long-term yields of Spanish, Italian, Irish, and Portuguese government bonds declined around 12% down to 6% to catch up with the German and French government bond yields. Throughout 1998, there was a strong co-movement in long-term yields. This was reflected in the smooth upward move in the total return connectedness from 58% at the end of 1997 to 65% at the end of April 1998. During this period the "net" connectedness of Spanish, Portuguese, and French 10-year bonds increased by more than 40 percentage points.

In the second half of 1998, the economic and financial troubles of the Russian government led to an eventual declaration of a debt moratorium in August 1998. Following the Russian debt crisis, Long-Term Capital Management (LTCM), an

[2] See Borio and McCauley (1996) for an analysis of the increased volatility over this period. Since we do not have data to calculate the range volatility for all 10 countries in and around 1994, we only analyze the return connectedness over this period.

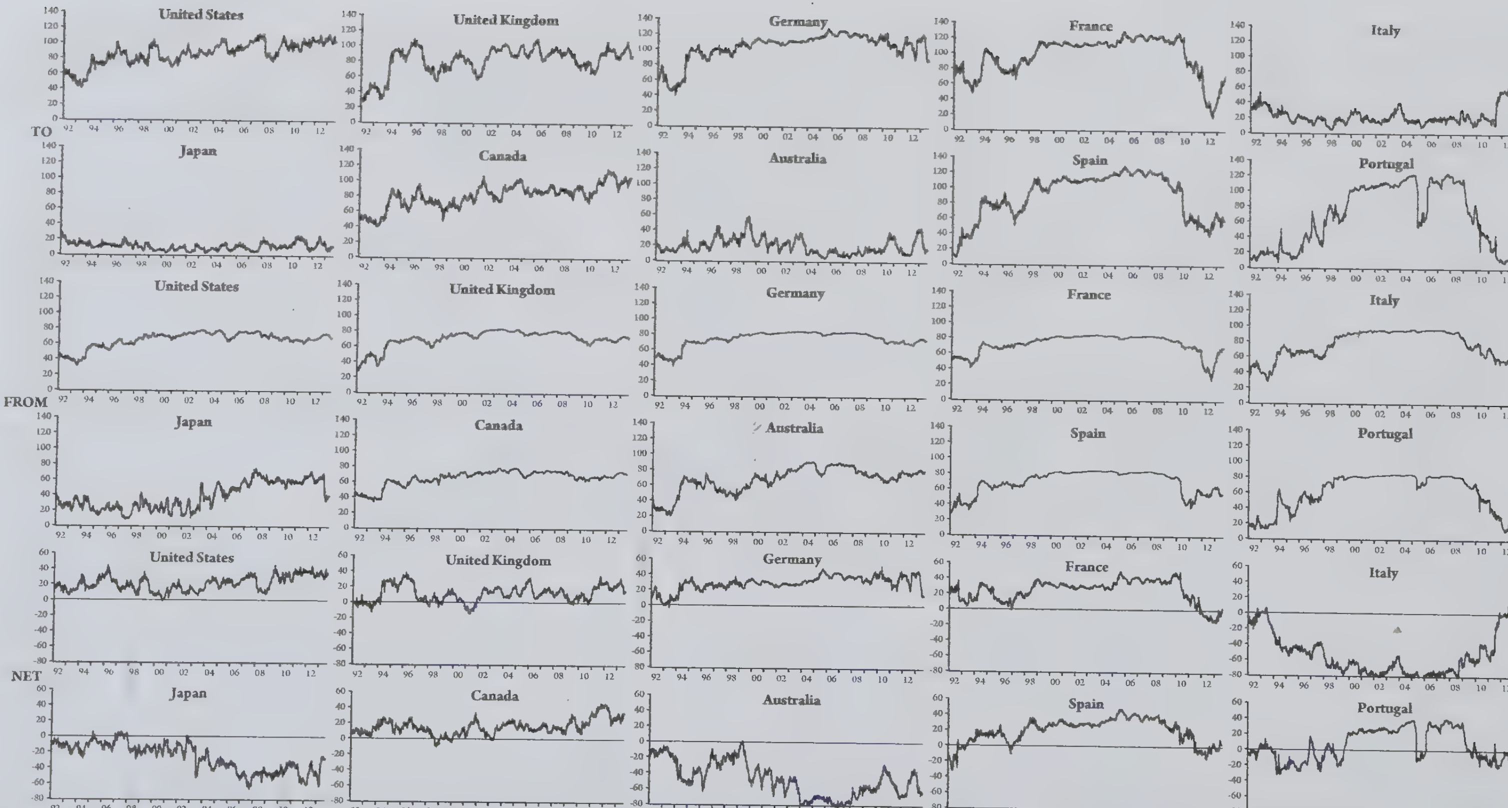


Figure 5.3 Total directional return connectedness (200-day window).

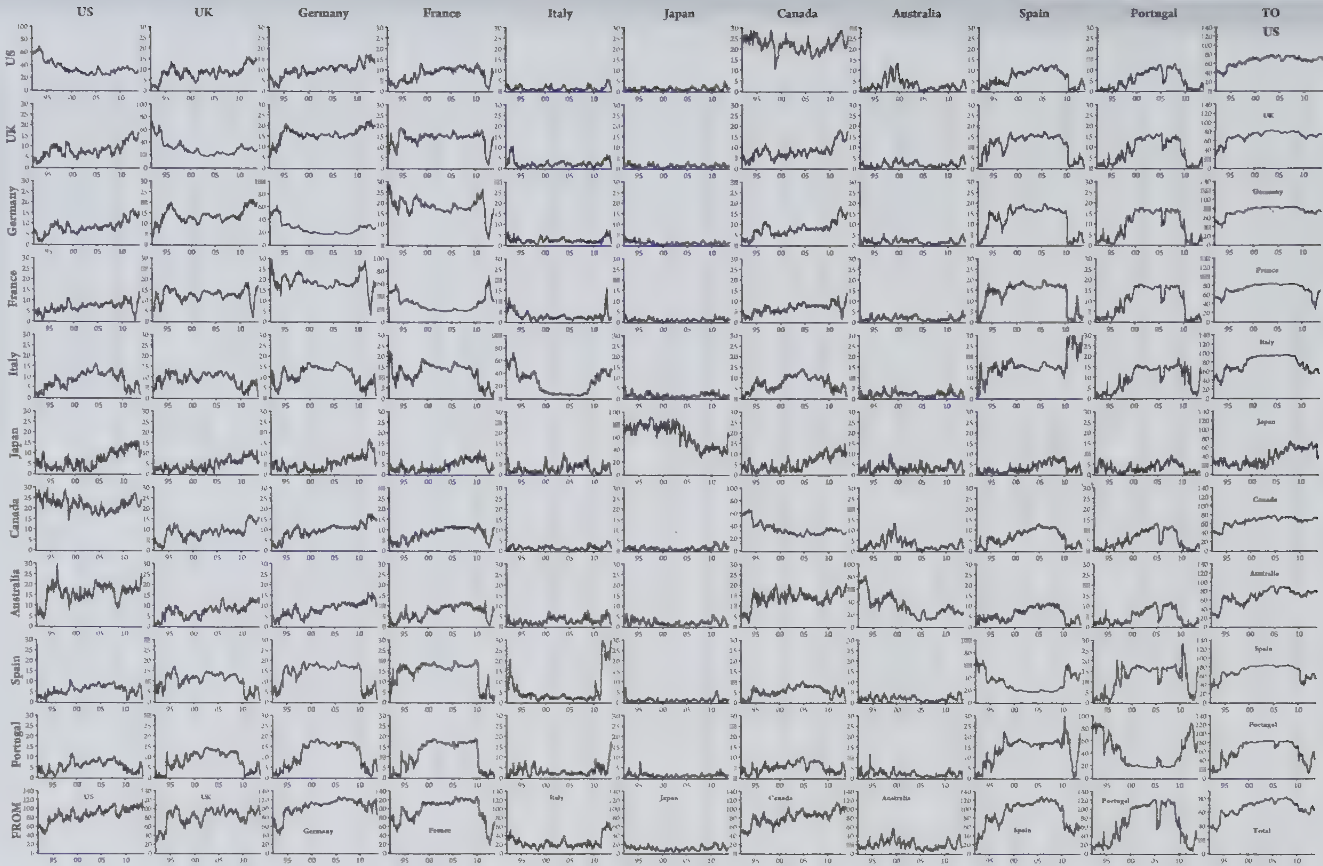


Figure 5.4 Pairwise directional bond return connectedness.

The diagonal elements of the matrix are the own-degree plots and they range between 0% and 100%; the off-diagonal elements are the pairwise connectedness plots and they range between 0% and 30%. Finally, the last column and the last row are the "from" and "to" connectedness plots, and their respective y-axes range between 0% and 140%.

American hedge fund with highly leveraged positions in Russian and other government bonds, collapsed, threatening the stability of the American financial system. Following the Russian and the LTCM crises, long-term interest rates jumped in unison, which was reflected in the sudden increase in total return connectedness, from around 62% in August to 71% by mid-October.

Following the jump in October 1998, the total return connectedness index moved slowly up over a period of 5 years. From around 70% in October 1998 the index reached 76% by May 2003. Following the convergence in long-term bond yields across the eurozone bond markets from 1995 until toward the end of 1998, a significant degree of co-movement was observed among these bond markets until 2003. The index went up from 76% to 81% in the second half of June 2003, during which time the FOMC conducted its meeting where it cut the Fed funds target rate by 25 basis points. Normally, we would have expected the long-term yields to go down as the policy rate was cut. However, as the FOMC informed public that it was getting very close to the end of rate cuts, the markets reacted to the rate cut in June with an increase in long-term yields. The long-term yields increased in the United States and abroad. As a result, the return connectedness went up along with the policy rates.

After keeping the policy rate constant for a year, the FOMC switched to a tight policy stance in its June 30, 2004 meeting. In each of the subsequent 16 meetings, the committee increased the Fed funds target rate by 25 basis points. The return connectedness index started to increase before the June 30 meeting. It increased from 77% in mid-June 2004 to 81% in mid-November. From late November 2004 to mid-2005, the return connectedness index declined by approximately 10 percentage points, from 81% to 71%. Initially, the Fed's monetary tightening did not achieve the expected result. For a brief period from November 2004 to June 2005, the U.S. 10-year bond yields fluctuated between 4% and 4.6%. We will discuss this important episode in more detail in the section on volatility connectedness (Section 5.4).

From mid-2005 to mid-2006 the 10-year bond yields increased again, from 4.0% to 5.2%. The return connectedness index also resumed its upward movement, reaching 82% by November 2007. However, following the Fed's December 11, 2007, January 22, and January 30, 2008 decisions to lower the Fed funds target rate by a total of 1.5 percentage points, 10-year U.S. bond yields started to go down quickly, whereas the long-term yields in other bond markets went up by around 1 percentage point. As a result, the so-called "decoupling" of the long-term government bond yields had taken place. The return connectedness index went down from 82% in December 2007 to as low as 56% as of July 2012.

The downward move was very strong despite the occasional upward ticks during the several rounds of the eurozone debt crisis that started in 2009. What had been achieved across major bond markets since the mid-1990s was completely undone.

The U.S. financial crisis and the ensuing Eurozone sovereign debt crisis effectively reversed the impact of globalization and the formation of the EMU on the return connectedness index. The daily returns on government bonds started to move in different directions. While the American, British, Japanese, and German government bond yields were still low, most of the other industrialized countries in our analysis experienced significant increases in their borrowing costs. Even French government bond yields decoupled from German and British bond yields since August 2011. As a result, what was experienced was nothing but the decoupling of the bond markets in highly indebted countries from the bond markets of countries that are still on a sound footing.

This is all evident in Figure 5.4. Irrespective of the direction of connectedness, the pairwise connectedness of the top four markets (United States, United Kingdom, Germany, and France) with the troubled three markets (Italy, Spain, Portugal) declined significantly in 2009 through 2011. In contrast, the pairwise connectedness of the top four markets among each other increased significantly. Similarly, the pairwise return connectedness among the troubled three also increased. This result shows that there has been a decoupling among the major bond markets since 2009.

From the beginning of our sample to the end, the pairwise connectedness of the top four markets with each other was high. Actually, the pairwise connectedness of the top three European bond markets (German, British, and French) were higher than that of the U.S. market. The Italian market had very little "to" connectedness with others, but its "from" connectedness with the European bond markets was quite high, showing that return shocks generated connectedness from others to the Italian bond market, and not vice versa. Only during the latest bout of the eurozone debt crisis in 2011 did the Italian market's "to" connectedness with the Spanish bond market increase substantially. In contrast to the Italian market, the Spanish and Portuguese bond markets had much higher pairwise connectedness with all other markets and especially with the European markets.

The U.S. market had substantial pairwise return connectedness "to" and "from" the Canadian bond market, as well as high pairwise "to" connectedness with the Australian market. The Japanese and Australian bond markets, on the other hand, had low "to" return connectedness. Both of these markets generated very little connectedness to others. However, similar to the Italian case, the Australian market had a high "from" connectedness from other markets, especially from the United States, Canada, and the top three European bond markets. Interestingly, the Japanese market had low "from" and "to" connectedness with all other countries in our sample. However, following the global financial crisis, the "from" connectedness of the Japanese bond market with the U.S., German, U.K., and Canadian markets started to move up steadily.

5.4 DYNAMICS OF VOLATILITY CONNECTEDNESS

5.4.1 Total Connectedness

Figure 5.5 plots the total volatility connectedness along with the total return connectedness. The first thing one observes in the graph is how closely the two connectedness series move. Second, the return connectedness is always higher than the volatility connectedness.

Starting at the beginning of the sample in mid-2000, the total volatility connectedness followed an upward trend that lasted until late 2004.[3] Over this period, the volatility connectedness increased from 46% in mid-2000 to 72% by October 2004.

The upward trend is also observed when we conduct the analysis with 100-day rolling windows (see Figure 5.6). Even though the 100-day rolling windows plot depicts

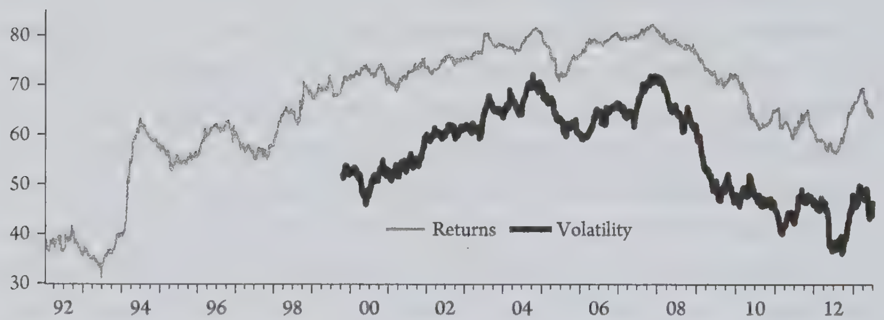


Figure 5.5 Total return and volatility connectedness (200-day window).

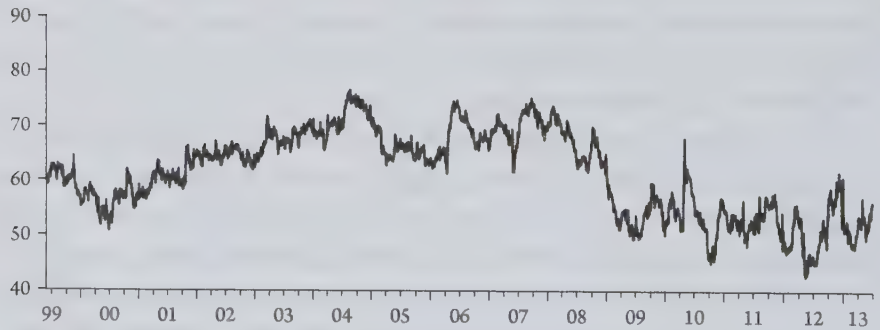


Figure 5.6 Total bond yield volatility connectedness (100-day window).

[3] As we have already noted above, the data on daily minimum and maximum yields needed to calculate the daily range volatility series are available only starting in 1999. Therefore, we are not in a position to gauge the impact of the introduction of the euro as the common currency of the European Monetary Union on bond market volatility and volatility connectedness.

more fluctuations in the index, both of these short-run fluctuations and the long-run trends are consistent with the one we obtained in the 200-day rolling window plots.

There were occasional short-lived drops during the five-year-long upward trend of the total volatility connectedness. The first drop in the aggregate volatility connectedness was observed during the tech-stock bubble burst in the first quarter of 2000. It was followed by others: after the 9/11 terrorist attacks, during the Iraq War in the first half of 2003, and following the reversal in the Fed's policy stance in mid-2004. We will discuss each episode in detail when we analyze the directional connectedness of each sovereign bond market later in this chapter.

The upward trend was followed by a 13-percentage-point decline in connectedness that lasted from September 2004 to early 2006, a period that was marked by the monetary tightening in the United States. In 17 consecutive meetings from June 30, 2004 through June 29, 2006, the FOMC increased the Fed funds target rate from 1.0% to 5.25%. Even though the Fed funds target rate increased by 425 basis points during this period, the long-term bond yields hardly changed. Indeed, from the end of June 2004 to January 2006, the 10-year government bond yields declined from 4.7% to 4.4%. The tight monetary policy finally had its effect on the long-term bond yields in the second half of 2006.

The whole episode has become known as "Greenspan's conundrum." Many studies have tried to explain the factors behind the apparent breakdown of the interest rate channel of the monetary transmission mechanism. We will discuss this episode in more detail below when we analyze the dynamics of the directional volatility connectedness.

The interest rate channel of the transmission mechanism became functional again as the FOMC continued to increase the target rate by 25 basis points in four consecutive meetings in the first half of 2006. The last two rate hikes (May 10, 2006 and June 29, 2006) had a significant impact on financial markets in the United States as well as around the world. Against the expectations of an overwhelming majority of market participants, the FOMC decided to increase the target rate by 25 basis points in May 2006 and announced that it might consider another rate hike in its subsequent meeting. The rate hike decision and the announcement of a likely future rate hike unnerved the markets and led to a widespread unwinding of the carry trade positions taken in many emerging markets. As a result, emerging stock, bond, and FX markets were faced with a widespread asset sell-off, which increased the volatility in many emerging markets. The Fed's rate hikes in the first half of 2006 also had an impact on volatility connectedness. As a result of the rate hikes, the volatility connectedness increased from 59% in early January to 65% at the end of June 2006.

In the second half of 2006 and early 2007, the total volatility connectedness across bond markets was quite steady. The unfolding of the global financial crisis in several stages in 2007 through 2008 has had its mark on the volatility connectedness of major sovereign bond markets. Between the early signs of the sub-prime crisis in March 2007 and the liquidity crisis of August 2007, the total volatility connectedness increased substantially, from 64% in March 2007 to 72% at the end of 2007, the highest level of the total volatility connectedness achieved between 1999 and 2012. During the temporary tranquility period following J.P. Morgan's takeover of Bear Stearns, the connectedness declined steadily to 61% on September 12, 2008, the Friday before the bankruptcy of Lehman Brothers was announced. With the announcement of Lehman's bankruptcy, the connectedness index increased to reach 65% in a month's time.

With the crisis becoming a serious threat to the global capitalist system, all asset classes experienced substantial volatility. The situation, however, was quite different in sovereign bond markets at the time. As the government bonds in industrial countries, and especially in the United States, were viewed as fully safe, all investors rushed to buy government bonds, pushing the yields all the way down. Along with the yields, volatility also declined and the total volatility connectedness of the sovereign bond markets declined sharply from 65% at the end of September to 47% by August 2009.

As the policy interest rate hit the zero bound, the Fed provided ample liquidity to the economy after the Lehman bankruptcy, increasing the monetary base sharply from $800 billion to $1600 billion. The Fed's decision to commit to a second round of quantitative easing (QE2) for an indefinite period caused the euro-dollar parity to reach 1.60 in July 2009. However, toward the end of the summer, worries about some of the peripheral EU member economies led to a quick sell-off of European bank stocks. The fact that European economies were doing no better than the U.S. economy increased the prospects of rate cuts by the ECB and led to a rather sharp depreciation of the euro against the U.S. dollar. As sovereign debt sustainability became part of the major policy dilemmas in the eurozone countries, the bond market volatility connectedness increased by five percentage points during this period, but the tensions subsided sharply soon.

Starting in December 2009, Greece's fiscal problems and its sovereign debt sustainability were at the center of global attention. As it became clear that the EU was not ready to deal with the Greek debt crisis, bond markets went through several rounds of gyrations and were on the brink of collapse in May 2010. From the beginning of 2010 to May 2010, total volatility connectedness increased again and stayed around 51% until the end of 2010.

Another round of gyrations was felt throughout the global financial system in the second half of 2011. This time around, Spanish and Italian bonds were at the center of global attention. Yields on 10-year Spanish government bonds increased above

6% in mid-July. The yield on 10-year Italian government bonds went above 6% market briefly at the beginning of August 2011. With assurances from the ECB, the EU markets regained their calm from August through October. However, the next wave of sell-offs in the two bond markets in November through December was even more cause for concern. The yields on 10-year government bonds in the two countries increased above 7%. The total volatility connectedness increased from 40% at the end of March to 49% in mid-September.

The increased volatility in financial markets around the world led to political changes in these two countries. Yielding to domestic and international pressure, Sylvio Berlusconi, the populist prime minister of Italy, had to resign. His government was replaced by a technocratic government led by Mario Monti, with backing from all major political parties. In the meantime, in the general elections held in November, Spain replaced its Socialist government with one led by the Prime Minister Mariano Rajoy of the People's Party. Even though these political changes were helpful in improving the situation in financial markets, what turned the tide in favor of tranquility was the intervention of the ECB, under the leadership of its new president Mario Draghi. On December 12, the ECB announced that it would make 500 billion euros available to eurozone banks through a program called a long-term refinancing operation (LTRO). The ECB added that there might be further rounds of LTROs in the near future. Once the news came out, all financial markets in the eurozone and beyond became calm. The volatility connectedness across bond markets started to decline in the second half of December and went down to 38% by the end of May 2012.

We have so far analyzed major movements of the total volatility connectedness in the bond markets from 1999 to 2012. Before moving to directional volatility connectedness, we will compare the total volatility connectedness in the bond and stock markets. There are two striking differences between the dynamic behavior of volatility connectedness in the two markets. First, the stock market volatility connectedness did not follow an upward trend like the one we observed in the bond markets. As we will see in detail later, the upward trend was a result of the increasing volatility connectedness of the European bond markets after the establishment of the EMU in 1999. Second, the volatility connectedness across bond markets increased only mildly (approximately 10 percentage points) during the global financial crisis, compared to a 25-percentage-point increase in the stock market volatility connectedness. Furthermore, after the collapse of Lehman Brothers, the bond market volatility connectedness declined by more than 20 percentage points, all the way down to levels below the ones it attained in the early 2000s, whereas the volatility connectedness of the global stock markets continued to stay high. As discussed above, the decline in the total bond market volatility connectedness was a result of the decoupling of the so-called "safe haven" bond markets from the ones that had unsustainably high government debt stocks.

5.4.2 Total and Pairwise Directional Connectedness

After setting the stage with a discussion on the dynamics of the total volatility connectedness, we are now ready to focus on the dynamics of the directional volatility connectedness over time. Figure 5.7 presents the directional volatility connectedness for each country over the rolling sample windows. We will analyze the total directional volatility connectedness along with the pairwise directional volatility connectedness measures presented in Figure 5.8.

It is important to understand the dynamics of the directional connectedness in comparison with the full-sample volatility connectedness table (Table 5.4). As an example, let us start with the German and French bond markets. What we observe in the volatility connectedness table is mostly carried over to the dynamic volatility connectedness plots. The German and French bond markets continued to be the leading markets in terms of the "to," "from," and "net" connectedness. They are the net transmitters of volatility shocks to other markets. Their "to" and "net" connectedness degrees fluctuated around 100% and 20%, respectively, for most of the period.

In terms of their total directional connectedness degrees, the two markets behaved quite similar until 2011. They both had high "to," "from," and "net" connectedness for most of the sample period (see Figure 5.7). Furthermore, from the pairwise connectedness measures, we observe that the German and French sovereign bond markets were highly connected in volatility at the beginning of the sample, and their connectedness to others has neither increased substantially nor fluctuated as much as the "to" connectedness of other bond markets over time. For example, their contributions to the upward trend in the total volatility connectedness from 2000 to mid-2004 were limited. Their contributions to the significant fluctuations in the total volatility connectedness in 2004 through 2007 were also less than the contributions of the American, British, and Canadian markets.

Both the "to" and "net" connectedness of the German and French bond markets declined significantly in the first half of 2009 following the end of the global financial crisis. However, both markets' "to" connectedness increased by close to 50 percentage points following the outbreak of the Greek debt crisis. It is interesting that while the Greek bond market had become completely marginalized since the outbreak of the debt crisis, investors around the world paid more attention to the volatility in the German and French sovereign bond markets. The pairwise volatility connectedness plots make it clear that the increase in directional volatility connectedness from German and French bond markets was channeled toward the American and British sovereign bond markets (see Figure 5.7).

This was a result of the EU's inability to devise a rescue operation that would help prevent Greece's fiscal problems from spreading to other member countries. As a

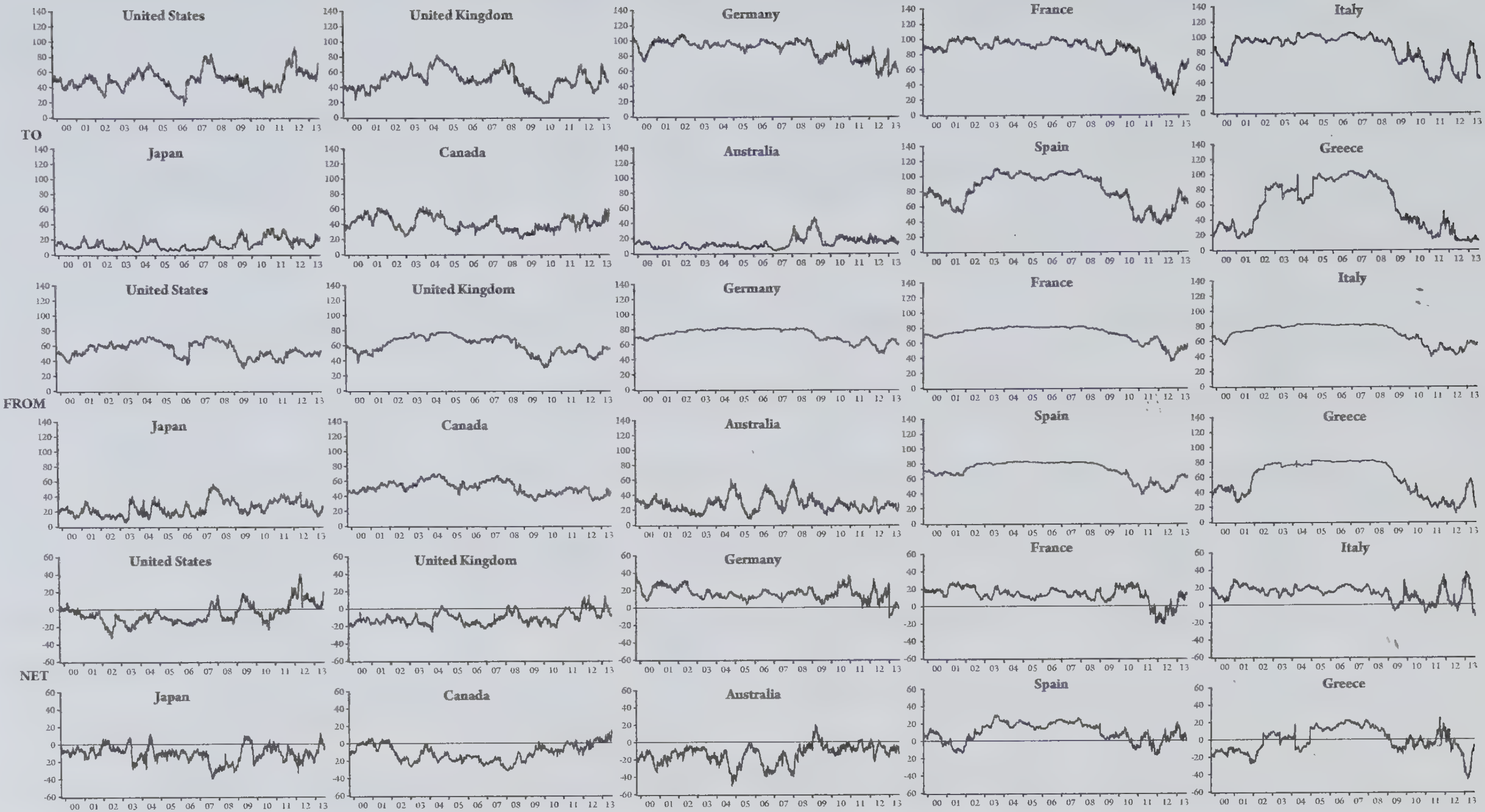


Figure 5.7 Directional bond yield volatility connectedness (200-day window).

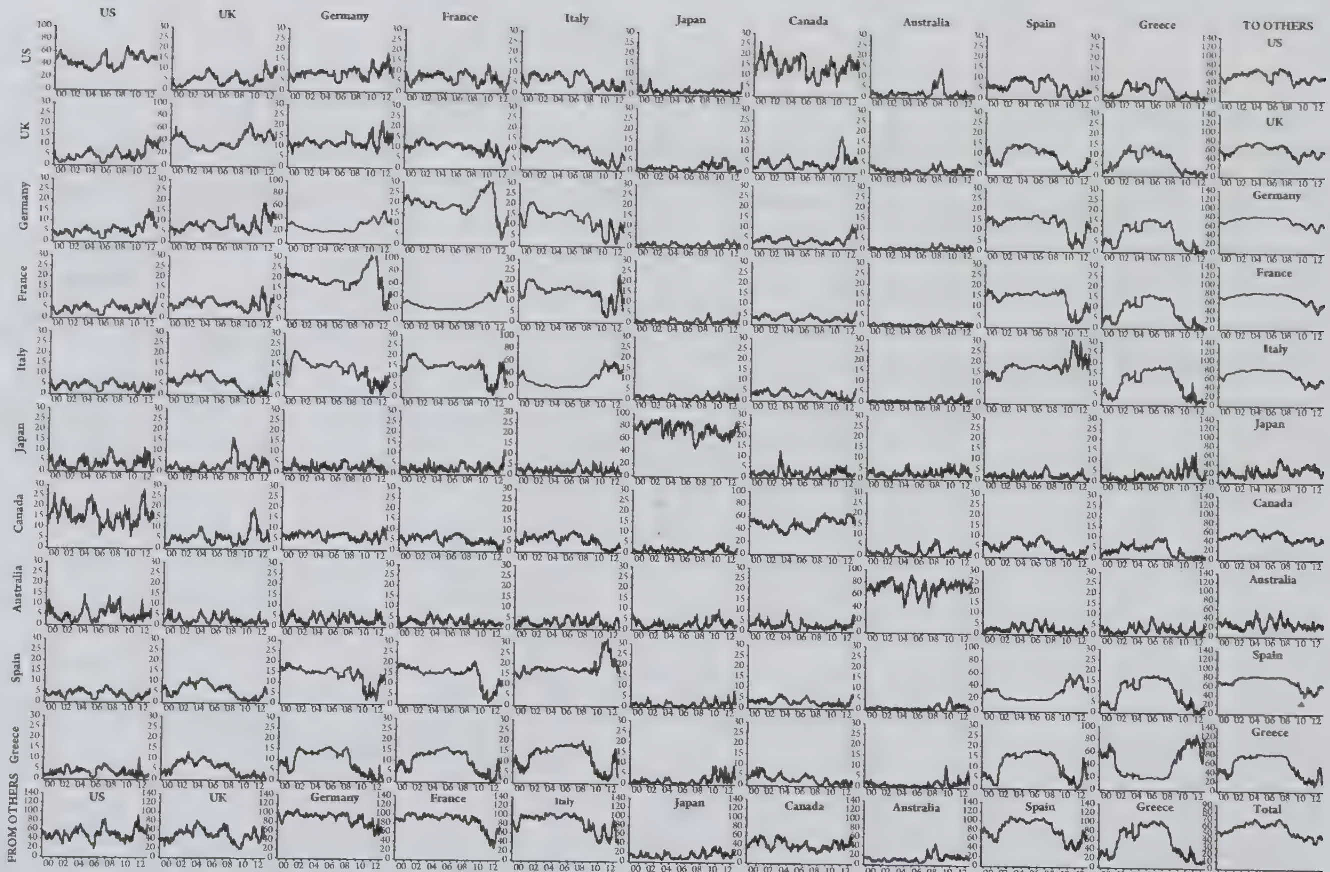


Figure 5.8 Pairwise bond yield volatility connectedness.

The diagonal elements of the matrix are the own-degree plots, and they range between 0% and 100%; the off-diagonal elements are the pairwise connectedness plots, and they range between 0% and 40%. Finally, the last column and the last row are the "from" and "to" connectedness plots, and their respective *y*-axes range between 0% and 140%.

result, highly indebted Irish and Portuguese government bonds came under heavy pressure, transforming the Greek debt crisis into a eurozone debt crisis. Developments in the peripheral countries led to uncertainty in financial markets of the key member countries, and this is reflected in the increased volatility connectedness of their bond markets.

However, once the Spanish and Italian bond markets came under pressure in the summer of 2011, the French bond market started to decouple from the German bond market in terms of "to-connectedness." Its "to" connectedness declined 30 percentage points, while that of the German bond market went up by 20 percentage points before coming down slightly in late 2011 and early 2012. Actually, the two bond markets decoupled in terms of the "to" connectedness in returns as well.

For an overwhelming portion of the sample, the volatility connectedness plot of the Italian bond market resembled the volatility connectedness plots of the German and French bond markets. Italian bond market generated net positive volatility connectedness from 1999 all the way to 2008. Following an increase in 2000, it attained high "to," "from," and "net" connectedness degrees until the climax of the global financial crisis in late 2008. Similar to the behavior of other markets, its "to" and "net" connectedness declined from late 2008 through the first half of 2009 and increased slightly following the Greek debt crisis of late 2009 and early 2010. However, from this point onward the Italian sovereign bond market started to decouple in volatility from the French and German bond markets. Its "to" connectedness declined vis-à-vis the two markets. From the second quarter of 2010, its "to" connectedness started to decline sharply, close to 50 percentage points. However, once Italy was caught in the whirlwind of the debt crisis in the summer of 2011, its volatility connectedness increased by 50 percentage points, a behavior similar to that of the Spanish, American, German, and British bond markets. The decoupling of the Italian bond market from the French and German bond markets and its recoupling with that of Spain show that in 2011 Italy had become part of the crisis, perhaps thanks to its high level of sovereign debt stock, both in levels and relative to its GDP.

The Greek sovereign bond market had low "to" and "from" connectedness to start with. While its "to" connectedness fluctuated around 20% until late 2001, its "from" connectedness fluctuated around 40%. As a result, its "net" connectedness was negative. At the beginning of 2002, its "from" connectedness increased sharply, quickly reaching 70%. It continued its upward movement throughout the year, reaching 80% by the end of the year. In the meantime, its "to" connectedness increased gradually, reaching 80% by the end of 2002 and surpassing 80% in early 2003.

During the 2001–2004 period, the Greek sovereign bond market was the market whose connectedness increased the most. As a result, its "to" volatility connectedness reached 100% by the end of 2004. Indeed, from 2001 through 2004, the Greek bond market contributed significantly to the upward trend in total volatility connectedness. Greece became a eurozone member country in 2001. Its volatility connectedness measures show that its bond market became integrated with bond markets within one year of its eurozone membership.

The "to" volatility connectedness of the Greek bond market fluctuated in a band between 80% and 100% until the end of 2008. Its "from" connectedness stayed around 80% until the end of 2008. As a result, from 2003 to the end of 2008, the Greek bond market had positive "net-connectedness."

The "to" and "from" volatility connectedness of the Greek sovereign bond market declined sharply in early 2009 to 40%. Its "to" connectedness slightly increased when the Greek debt crisis started in late 2009. However, once it became evident that Greece's fiscal problems were deeper than the official statistics revealed, the Greek sovereign bond market decoupled from other eurozone bond markets; its "to" connectedness went down to less than 20% by the end of 2010.

The dynamic behavior of the directional volatility connectedness of the 10-year Spanish sovereign bonds was very different from that of other markets. Its "to" connectedness was almost always below 20%. Its "from" connectedness fluctuated around 20%. As a result, its "net" connectedness was slightly negative throughout the whole sample period considered. It looks as if the Spanish sovereign bond market was never able to integrate with other bonds markets in terms of volatility throughout most of the sample period. Things changed in the summer of 2011, when the euro debt crisis spread to Spain and Italy. Both its "to" and "from" connectedness jumped to 50% level in the summer of 2011 and stayed high (around 30%–40%) until the end of February 2012.

Having discussed the continental European bond markets, we can now focus on the directional connectedness of the other bond markets in our sample. While the German and French markets consistently had high "to" connectedness degrees throughout the sample period, the connectedness of the American, British, and Canadian government bond markets were lower, yet they fluctuated substantially over time.

The volatility connectedness of the American bond market followed three cycles between 2000 and 2006. The rather big drop in the Nasdaq stock market index had its effect on other stock markets, leading to an increase in stock market volatility. The increased stock market volatility throughout 2000 led to an increase in volatility connectedness from the stock market to the bond market (see Figure 2.4). In the single asset framework of this chapter, the increased U.S. bond market volatility is translated into an increase in the volatility connectedness of the American sovereign bond market during the period August 2000 to July 2001.

Faced with a recession that stemmed in part from market sentiment, the FOMC in consecutive meetings cut the fed funds target rate from 6.5% at the beginning of the year to 1.75% by the end of the year. As a result, the U.S. bond market volatility declined significantly in the second half of 2001; with it, the connectedness of the U.S. bond market also declined.

During the 9/11 terrorist attacks, U.S. bond market volatility did not increase much. However, the Enron accounting scandal of November 2001 and the World-Com accounting scandal and bankruptcy of July 2002 worsened stock market sentiment in the United States. In 2002 as a whole, the S&P 500 index declined by close to 1/3 of its value at the beginning of the year. The resulting volatility in the stock market again led to a high connectedness from the stock market to the bond market (see Figure 2.4). The resulting increase in the U.S. bond market volatility, in turn, led to an increase in the connectedness between the U.S. bond market and the others, which lasted until mid-2003.

Now we can focus on the period 2004–2006, during which the link between the short-term and long-term interest rates was broken. Alan Greenspan, the chairman of the Federal Reserve at the time, called this phenomenon a conundrum. During this period, the American sovereign bond market experienced a decline in its connectedness to other bond markets. However, other bond markets also experienced an increase in their volatility connectedness to and from other bond markets: The British and Canadian markets' gross and "net" connectedness to others also declined from mid-2004 until the beginning of 2006. However, the British and Canadian markets did not follow the American bond market from January 2006 onward, as its connectedness started to increase and the relationship between short and long rates was reestablished.

At the time, Greenspan suggested that the failure of long-term yields to respond to short-term rate cuts might be due to the foreign governments' and sovereign wealth funds' purchases of long-term U.S. bonds. Later on, however, Rudebusch et al. (2006) showed that the decline in bond yield volatilities across major sovereign bond markets lay at the root of the Greenspan conundrum. Our finding that there was a significant decline in volatility connectedness among the major bond markets during the period of the Greenspan conundrum lends support to the Rudebusch et al. (2006) viewpoint. As we have argued in previous chapters, the volatility connectedness is asymmetric; during times of increased uncertainty, asset markets become more connected in volatility, whereas in tranquil times they become more detached from each other. The fact that the total volatility connectedness declined from late 2004 through early 2006 reflects a decline in the volatility of the sovereign bond yields in major markets.

While the German and French bond markets were net transmitters of volatility shocks throughout the 1999–2010 period, the "net" volatility connectedness of the American bond market was negative before the global financial crisis of 2007–2009. The "net" connectedness of the American bond market moved into positive territory only after the liquidity crisis of August 2007 and after Lehman Brothers' bankruptcy in September 2008. However, with the gradual intensification of the Greek and euro-zone debt crises, the "net" connectedness of the American market fluctuated around zero for most of 2010 and the first half of 2011, before increasing to around 30% in the second half of 2011. When we take a closer look at the pairwise connectedness plots in Figure 5.8, it becomes clear that the decline in the "net" connectedness of the American bond markets in great part resulted from an increase in the "to" volatility connectedness of the French and German sovereign bond markets.

The temporal behavior of the pairwise and total directional volatility connectedness measures of the Japanese and Australian bond markets were significantly different from other markets in the analysis. Their plots show how detached they were from other markets for most of our period of analysis. Both pairwise and total directional "to" connectedness of the two countries were quite low for most of the period. Starting in late 2007 and lasting until the collapse of Lehman Brothers, the Australian bond market had some sizeable (as high as 15%) "to" volatility connectedness with the U.S. bond market. Other than that its pairwise "to" connectedness with other bond markets was rather weak. Japan had low pairwise "to" and "from" connectedness with all countries for most of the time period considered. Its highest pairwise "from" connectedness was with the U.K. bond market in 2008 (close to 20%), followed by Greece after 2010 (around 15%) and the United States in 2007 (around 10%).

Canada also had low "to" and "from" connectedness with other countries. The only exception to this rule was its connectedness with the United States. Throughout the period of the analysis, the pairwise "to" and "from" connectedness measures between Canada and the U.S. were quite high, fluctuating between 10% and 25%. Given the high degree of economic and financial integration between the two neighboring countries, it is no surprise to have a high level of pairwise volatility connectedness between the two bond markets.

5.A APPENDIX: STANDARD ERRORS AND ROBUSTNESS

In this appendix, we first present the full-sample return and volatility connectedness tables in Tables 5.A.1 and 5.A.2, along with the nonparametrically bootstrapped standard errors for total and pairwise connectedness measures.

As has been the case in previous chapters, an overwhelming majority of bond return and volatility connectedness measures are statistically significant at the 1% or 5%

Table 5.A.1 Return Connectedness Table with Standard Errors, 10-Year Government Bonds

	USA	*UK*	*GER*	*FRA*	*ITA*	*JPN*	*CAN*	*AUS*	*SPA*	*PRT*	*FROM*
USA	42.9**	8.6**	11.3**	7.9**	0.0	0.2*	25.3**	2.0**	1.6**	0.2**	57.1**
	(0.75)	(0.41)	(0.37)	(0.36)	(0.04)	(0.08)	(0.46)	(0.27)	(0.28)	(0.07)	(0.75)
UK	9.0**	38.8**	20.6**	16.6**	0.2	0.2*	8.3**	0.9**	5.2**	0.3**	61.2**
	(0.40)	(0.75)	(0.35)	(0.39)	(0.09)	(0.08)	(0.39)	(0.19)	(0.49)	(0.10)	(0.75)
GER	10.3**	18.2**	34.2**	22.1**	0.2	0.3**	8.6**	1.1**	4.8**	0.3**	65.8**
	(0.37)	(0.39)	(0.54)	(0.41)	(0.09)	(0.10)	(0.35)	(0.18)	(0.52)	(0.10)	(0.54)
FRA	7.4**	15.0**	22.6**	35.0**	1.9**	0.3**	6.6**	1.0**	9.8**	0.4**	65.0**
	(0.35)	(0.40)	(0.40)	(0.61)	(0.29)	(0.09)	(0.34)	(0.18)	(0.58)	(0.12)	(0.61)
ITA	5.3**	6.2**	6.7**	10.2**	48.4**	0.2*	4.6**	0.7**	17.1**	0.6**	51.6**
	(0.44)	(0.50)	(0.51)	(0.55)	(1.49)	(0.10)	(0.40)	(0.18)	(0.90)	(0.20)	(1.49)
JPN	4.2**	1.7**	2.8**	1.9**	0.2	85.5**	2.4**	0.9**	0.3**	0.2	14.5**
	(0.48)	(0.32)	(0.37)	(0.33)	(0.13)	(1.56)	(0.38)	(0.26)	(0.14)	(0.12)	(1.56)
CAN	25.7**	8.7**	10.1**	7.5**	0.1	0.2*	43.6**	2.1**	1.8**	0.2*	56.4**
	(0.44)	(0.42)	(0.38)	(0.38)	(0.07)	(0.09)	(0.80)	(0.30)	(0.28)	(0.08)	(0.80)

continued

Table 5.A.1 (continued)

	USA	*UK*	*GER*	*FRA*	*ITA*	*JPN*	*CAN*	*AUS*	*SPA*	*PRT*	*FROM*
AUS	17.3**	7.0**	8.5**	5.7**	0.5**	0.4**	14.8**	44.0**	1.5**	0.2*	56.0**
	(0.52)	(0.42)	(0.43)	(0.38)	(0.17)	(0.13)	(0.50)	(1.40)	(0.26)	(0.09)	(1.40)
SPA	2.7**	7.0**	7.3**	14.7**	10.3**	0.1	2.6**	0.6**	53.3**	1.5**	46.7**
	(0.37)	(0.61)	(0.71)	(0.76)	(1.16)	(0.06)	(0.34)	(0.18)	(1.49)	(0.35)	(1.49)
PRT	0.5**	0.6**	0.7**	1.1**	0.9**	0.1	0.5**	0.3	2.5**	92.8**	7.2**
	(0.17)	(0.22)	(0.24)	(0.26)	(0.28)	(0.09)	(0.17)	(0.16)	(0.50)	(1.09)	(1.09)
TO	82.4**	73.1**	90.5**	87.6**	14.2**	2.0**	73.7**	9.5**	44.6**	4.0**	
	(1.68)	(1.97)	(1.64)	(1.80)	(1.41)	(0.48)	(1.67)	(1.14)	(1.93)	(0.68)	
NET	25.3**	11.9**	24.7**	22.6**	−37.4**	−12.6**	17.3**	−46.5**	−2.1*	−3.2**	48.2**
	(1.35)	(1.39)	(1.28)	(1.36)	(2.09)	(1.46)	(1.22)	(1.68)	(0.84)	(0.63)	(0.64)

Notes: The sample is taken from April 4, 1991 through June 28, 2013. Bootstrapped standard errors are presented in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively.

Table 5.A.2 Volatility Connectedness Table with Standard Errors, 10-Year Government Bonds

	USA	*UK*	*GER*	*FRA*	*ITA*	*JPN*	*CAN*	*AUS*	*SPA*	*GRC*	*FROM*
USA	45.4**	5.7**	10.3**	8.8**	6.0**	0.2	14.3**	1.8**	5.4**	2.2**	54.6**
	(1.98)	(0.59)	(0.67)	(0.65)	(0.54)	(0.12)	(0.97)	(0.45)	(0.52)	(0.36)	(1.98)
UK	5.1**	38.1**	14.4**	12.3**	8.9**	0.3	4.2**	1.8**	9.9**	5.0**	61.9**
	(0.51)	(1.72)	(0.60)	(0.56)	(0.54)	(0.15)	(0.49)	(0.40)	(0.56)	(0.51)	(1.72)
GER	5.6**	9.2**	27.2**	19.9**	13.5**	0.1	4.0**	0.7**	13.9**	6.0**	72.8**
	(0.49)	(0.63)	(0.67)	(0.44)	(0.47)	(0.07)	(0.38)	(0.23)	(0.45)	(0.44)	(0.67)
FRA	5.2**	8.2**	20.4**	28.4**	14.3**	0.1	3.8**	0.8**	13.8**	5.0**	71.6**
	(0.51)	(0.60)	(0.55)	(0.65)	(0.48)	(0.05)	(0.39)	(0.26)	(0.46)	(0.43)	(0.65)
ITA	3.3**	5.3**	13.3**	13.7**	30.9**	0.23	2.6**	0.2	19.1**	11.5**	69.1**
	(0.44)	(0.56)	(0.59)	(0.52)	(0.85)	(0.15)	(0.35)	(0.14)	(0.60)	(0.73)	(0.85)
JPN	1.5**	0.9*	0.4	0.4	1.2*	89.2**	0.4**	1.0*	0.7*	4.5**	10.8**
	(0.56)	(0.40)	(0.20)	(0.22)	(0.53)	(1.67)	(0.25)	(0.46)	(0.33)	(0.98)	(1.67)
CAN	16.7**	5.4**	7.8**	7.2**	5.1**	0.2	50.1**	0.9**	4.8**	1.9**	50.0**
	(1.03)	(0.56)	(0.55)	(0.51)	(0.45)	(0.13)	(1.65)	(0.28)	(0.43)	(0.33)	(1.65)

continued

Table 5.A.2 (continued)

	USA	*UK*	*GER*	*FRA*	*ITA*	*JPN*	*CAN*	*AUS*	*SPA*	*GRC*	*FROM*
AUS	6.3**	4.3**	4.4**	4.0**	2.5**	0.5	2.8**	71.0**	3.3**	1.1**	29.0**
	(0.90)	(0.75)	(0.75)	(0.73)	(0.59)	(0.26)	(0.61)	(3.34)	(0.65)	(0.37)	(3.34)
SPA	3.1**	6.2**	14.2**	13.9**	19.8**	0.2	2.5**	0.5*	29.4**	10.3**	70.6**
	(0.41)	(0.56)	(0.48)	(0.45)	(0.54)	(0.14)	(0.32)	(0.22)	(0.78)	(0.66)	(0.78)
GRC	1.3**	3.5**	6.5**	5.7**	15.1**	1.2*	1.0**	0.1	12.2**	53.5**	46.6**
	(0.33)	(0.62)	(0.64)	(0.60)	(1.05)	(0.56)	(0.24)	(0.09)	(1.00)	(2.42)	(2.42)
TO	48.1**	48.7**	91.5**	86.0**	86.2**	3.0**	35.6**	7.6**	83.0**	47.4**	
	(3.05)	(3.38)	(2.86)	(2.51)	(2.81)	(0.93)	(2.48)	(1.70)	(2.79)	(2.78)	
NET	–6.5*	–13.2**	18.7**	14.4**	17.1**	–7.9**	–14.4**	–21.4**	12.4**	0.8	53.7**
	(2.73)	(2.69)	(2.68)	(2.44)	(2.91)	(1.82)	(2.10)	(3.67)	(2.80)	(3.18)	(0.92**

Notes: The sample is taken from January 4, 1999 through June 28, 2013. ** and * indicate significance at the 1% and 5% levels, respectively. ** next to the row heading indicates that all entries of the row are significantly different from zero at the 1% level.

level. There are a few exceptions: Italy's pairwise bond return connectedness "to" the United States, the United Kingdom, Germany, Japan, and Canada, Japan's pairwise connectedness "to" Spain and Portugal, and Australia's connectedness "to" Portugal. In the case of the volatility connectedness table, Japan's connectedness to all others but Greece was statistically not different from zero.

All total directional return connectedness measures are also statistically significant. In the volatility connectedness table, only Greece's "net" connectedness to others is not statistically significant.

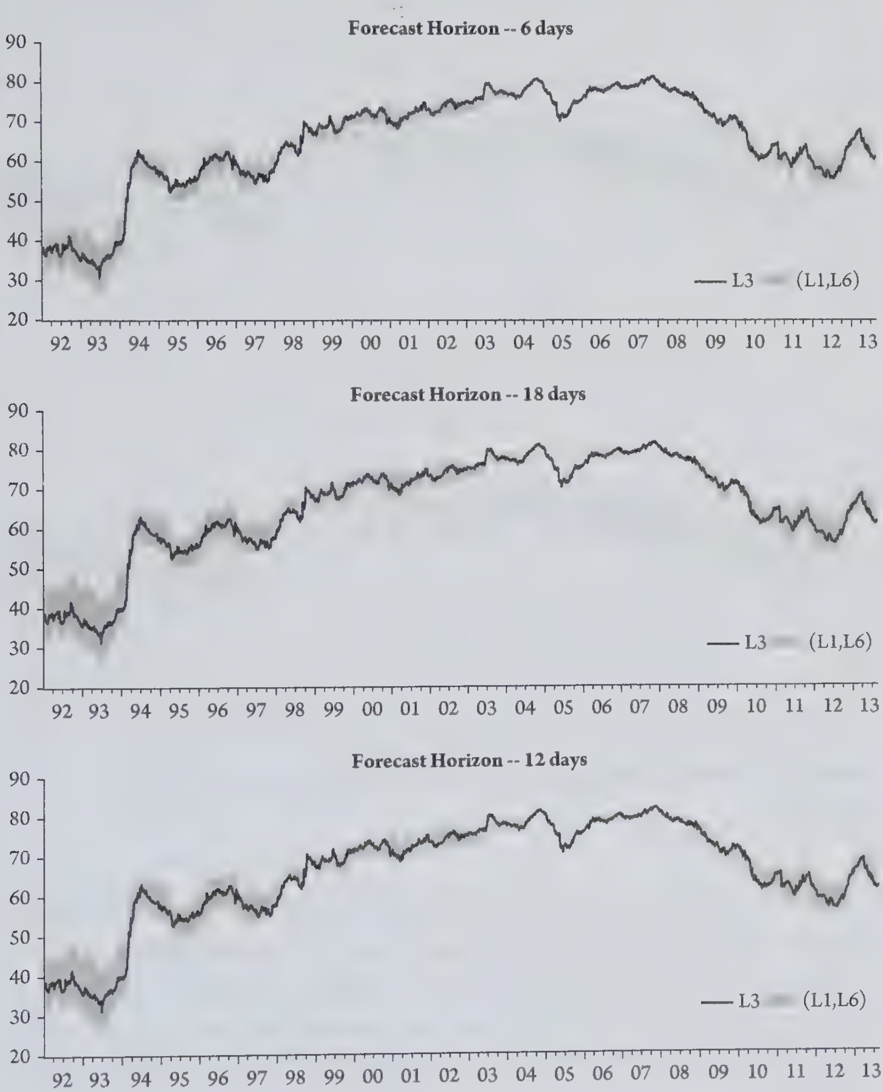


Figure 5.A.1 Robustness to forecast horizon and lag choice, total bond return connectedness. See the caption of Figure 2.A.1.

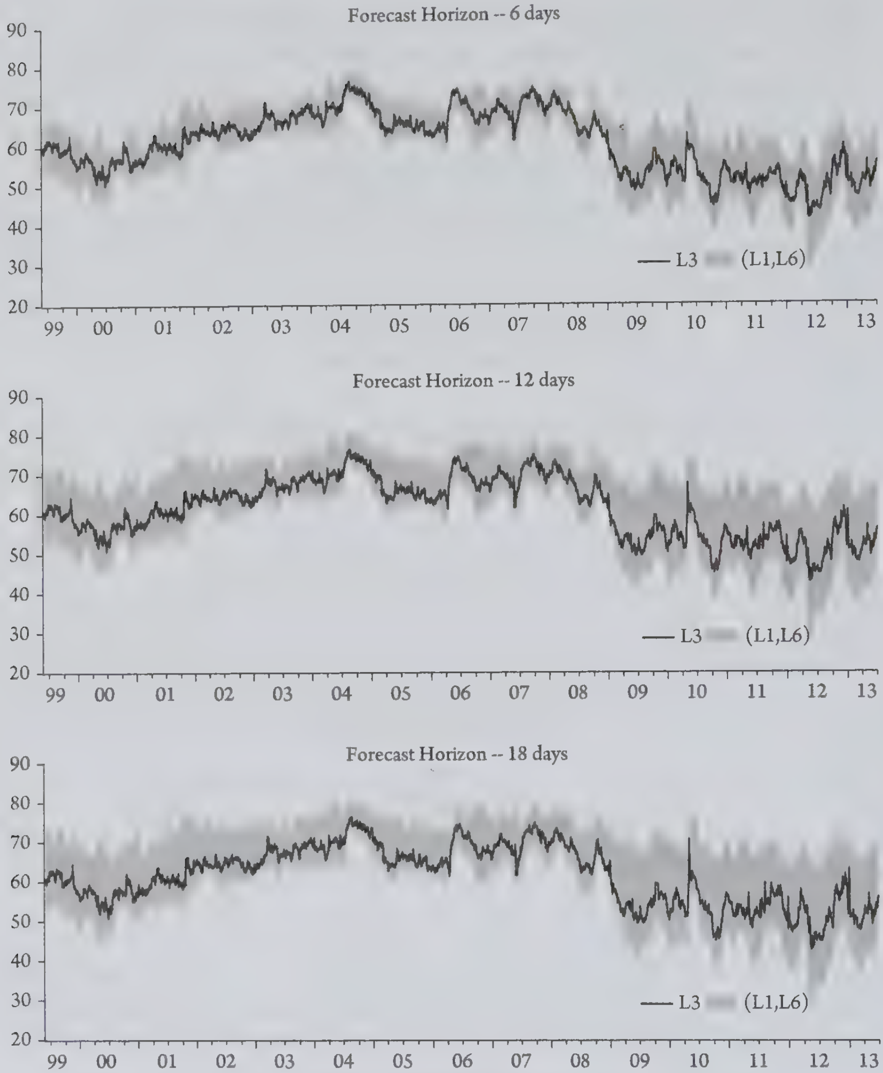


Figure 5.A.2 Robustness to forecast horizon and lag choice, total bond return volatility connectedness.
See the caption of Figure 2.A.1.

Figures 5.A.1 and 5.A.2 present robustness of the total bond return and volatility connectedness plots to variation in forecast horizon, *H*, and the VAR model order, *p*. Figure 5.A.1 clearly shows that a total return connectedness plot is very robust to changes in both parameters. There is not much change in the time-series behavior of the gray-shaded band and the black line as we change the forecast horizon from 6 to 12 days and 18 days. Furthermore, the gray-shaded band of VAR order 1 and 6 in all three graphs are slightly wide to begin with, but they get narrower as the window is rolled to include the late 1990s and stayed quite narrow throughout the most of 2000s. Only in

2010 through 2013 the band became wider, but not wide enough for the robustness of the bond return connectedness fail.

It is quite difficult to make a similar observation for the volatility connectedness plots in Figure 5.A.2. The volatility connectedness plot for our benchmark VAR(3) model varies very little with the change in the forecast horizon, H. However, the shaded band is wider in volatility connectedness plots in Figure 5.A.2 (especially for $H = 12$ and $H = 18$). These plots indicate that the total volatility connectedness is more sensitive to the variations in the VAR model order, p.

6

FOREIGN EXCHANGE MARKETS

Following the detailed analyses of connectedness across the global stock and bond markets in the previous two chapters, we now focus on the volatility connectedness of exchange rates of major currencies vis-à-vis the U.S. dollar. We decided to study the volatility connectedness across major exchange rates because the foreign exchange (FX) market has some unique characteristics that distinguish it from others. The FX market is unique in that it not only entails trades for the purposes of direct speculation in the value of currencies, but also assists international trade and investment around the world. Furthermore, the FX markets around the world are closer to a truly global market than the stock or bond markets. In 2010, 65% of daily FX market turnover took place through cross-border transactions. With $4 trillion in daily market turnover, the global FX market is the most liquid financial market. Finally, unlike the stock and bond markets, the FX markets are subject to direct intervention by central banks. Even though major currencies are allowed to float freely, there are times when central banks decide to intervene in the FX markets unilaterally or in a coordinated fashion. The impact of the infrequent central bank interventions on the FX market have been analyzed extensively. In this chapter, we hope to also study the implications of the solo or coordinated central bank interventions on the volatility connectedness of major exchange rates.

6.1 GLOBALIZATION AND FX MARKET VOLATILITY

6.1.1 Recent Developments in FX Markets

The foreign exchange market is a worldwide, over-the-counter financial market for trading currencies. It is a decentralized market, with no central clearing house and no single physical or electronic marketplace where brokers/dealers negotiate with each other to complete transactions. Other characteristics that make the global FX market unique include its 24-hour continuous operation excluding weekends, the possibility of central bank interventions, and very low return margins. With its 24-hour continuous operation, the global FX market is the market that gets closest to the definition of continuous-time process models. Because of its low return margins, the FX market is generally accepted as the financial market that comes closest to the ideal case of perfect competition.

As a result of the globalization process, the global FX market turnover has increased tremendously over the last two decades. According to the Triennial Central Bank Survey published by the Bank for International Settlements, average daily turnover in global foreign exchange markets as of April 2013 is estimated to be $5.35 trillion. One can appreciate how large the FX market trading volume is when she compares it with the same month average of $218 billion in total daily value of share trading in the world equity markets.[1] The latest data reveal 35% growth over the $3.97 trillion daily turnover in April 2010, along with 331% growth over the $1.24 trillion daily turnover in April 2001. Of the $5.35 trillion daily turnover, 42% was accounted by FX swap transactions, followed by spot transactions, 38%, outright forward transactions, 13%, and FX options and other transactions, 7% (see Table 6.1).

6.1.2 Literature on FX Market Volatility

The literature on intra-FX market volatility spillovers dates back to the 1990s. Until recently, parametric volatility measures have been predominantly used in the analysis of FX market volatility spillovers. In one of the earlier contributions, using a latent factor model of foreign exchange rate volatility, Diebold and Nerlove (1989) showed that the volatility of exchange rate returns was correlated. In another early contribution, Engle et al. (1990) used the GARCH model to specify intra-day exchange rate volatility. Their results support the meteor shower hypothesis, which posits the

[1] See Monthly Statistics of the World Federation of Exchanges.

Table 6.1 Reported Foreign Exchange Market Turnover by Currency Pairs

	2001		2004		2007		2010		2013	
	Amount	%	*Amount*	%	*Amount*	%	*Amount*	%	*Amount*	%
USD/EUR	372	30	541	28	892	27	1098	27.7	1289	24.1
USD/JPY	250	20	328	17	438	13	567	14.3	978	18.3
USD/GBP	129	10	259	13	384	12	360	9.1	472	8.8
USD/AUD	51	4	107	6	185	6	248	6.3	364	6.8
USD/CAD	54	4	77	4	126	4	182	4.6	200	3.7
USD/CHF	59	5	83	4	151	5	166	4.2	184	3.4
USD/SEK	6	0	7	0	57	2	45	1.1	55	1.0
USD/OTH	193	16	300	16	612	19	704	17.7	1113	20.8
EUR/JPY	36	3	61	3	86	2	111	2.8	147	2.8
EUR/GBP	27	2	47	2	69	2	109	2.7	102	1.9
EUR/SEK	13	1	30	2	62	2	71	1.8	71	1.3
EUR/OTH	22	2	44	2	123	4	163	4.1	179	3.3
Other pairs	28	2	50	3	139	4	149	3.7	195	3.6
All pairs	1239	100	1934	100	3324	100	3971	100	5345	100

Notes: Daily averages in April, in billions of U.S. dollars and percent. (Adjusted for local and cross-border inter-dealer double-counting (i.e., "net–net" basis).)

presence of intra-daily volatility spillover from one market to another, as opposed to the heat wave hypothesis, which argues for the volatility to have only country-specific autocorrelation. Baillie and Bollerslev (1991) analyzed the volatility spillovers in the FX market in detail and cannot find sufficient evidence in favor of systematic volatility spillovers among the exchange rates. Hong (2001), however, found strong evidence for the simultaneous interaction and cross-correlation between the Deutsche mark and the Japanese yen where the direction of the volatility spillovers ran from the Deutsche mark to the Japanese yen.

Following Diebold and Nerlove (1989), Dungey and Martin (2004) proposed a multifactor model of exchange rates in order to measure the contagion during the 1997–98 East Asian currency crisis, and they found strong statistical evidence supporting the presence of volatility spillovers. In a recent study, Kitamura (2010) examines the intra-day interdependence and the volatility spillovers among the euro, the British pound, and the Swiss franc by applying a varying-coefficient MGARCH model for the period July 2008 through July 2009. He found that there is a significant volatility spillover transmitted from the euro to the pound and to the Swiss franc. Inagaki (2007) applied a residual–correlation approach to examine the spillovers among the pound and the euro exchange rates, vis-à-vis the U.S. dollar, for the period from January 1999 through December 2004. He found support for volatility spillovers from the euro to the pound.

With an alternative approach, Bekiros and Diks (2008) investigated the causal relationship among the six major exchange rates[2] over two distinct sample periods between March 1991 and March 2007. Their results point to the significance of bi- and unidirectional volatility linkages (spillovers) among various exchange rate pairs.

Nikkinen et al. (2006) examine the expected volatility linkages among the exchange rates of the euro, the pound, and the Swiss franc against the U.S. dollar based on implied volatility for the period from January 2001 through September 2003. They find strong volatility linkages among these major European currencies where the euro is the dominant volatility transmitter.

All of the studies cited above rely on parametric volatility models. Recently, there has been more work that uses nonparametric measures in the analysis of FX market volatility spillovers. Melvin and Melvin (2003) examined volatility spillovers of the exchange rates of the Deutsche mark and the Japanese yen against the U.S. dollar across regional markets, consisting of Asia, the Asia–Europe overlap, Europe, the Europe–America overlap, and America, by using nonparametric volatility measures.[3]

[2] Australian dollar (AUD), euro (EUR), British pound (GBP), Canadian dollar (CAD), Swiss franc (CHF), and the Japanese yen (JPY) vis-à-vis the U.S. dollar.

[3] Melvin and Melvin (2003) based their analysis on Engle et al. (1990). Also, Cai et al. (2008) study the same issue, and their results are very close to the results of Melvin and Melvin (2003).

Their results provide evidence for both the intra- and inter-regional spillovers for both exchange rates, where the effects of the former are observed to be more prominent in volatility dynamics. McMillan and Speight (2010) apply the Diebold and Yilmaz spillover index methodology to examine the volatility spillovers among the three major exchange rates of the euro vis-à-vis three major currencies consisting of the U.S. dollar, the Japanese yen, and the pound for the period from January 2002 to April 2006. Their results suggest that there are strong volatility spillovers from the U.S. dollar to others in the whole sample.

Moreover, Bubàk et al. (2011) investigated the volatility spillovers in the Central European FX market[4] by using nonparametric volatility measures for the period January 2003 through June 2009. Their results suggest that there are significant volatility spillovers among Central European currencies, whereas the euro does not significantly affect the volatility of these exchange rates. They also show that the volatility spillovers among the Central European currencies tend to increase with market uncertainty.

6.1.3 Interest Rate Differentials and the Exchange Rates

Over the course of the latest wave of globalization and especially in the 2000s, the dynamics of the major foreign exchange markets have evolved steadily. While long-run swings used to be the main characteristics of exchange rates in the 1980s and 1990s, in the 2000s and especially after the global financial crisis, exchange rates of the major currencies started to fluctuate substantially in the short run. Even though the global financial crisis was over in mid-2009, the volatility of the daily foreign exchange market is still significantly higher than what it was before the crisis.

Interest rate differentials across countries have significant implications for the behavior of exchange rates over time. In order to take advantage of interest rate differentials, investors move huge sums of money across countries. To understand the interaction between interest rate differentials and the exchange rate movements, it is important to distinguish the country/currency pairs with low differentials from the ones with high differentials.

For those country pairs with similar underlying risk characteristics and hence low interest rate differentials, differences in output gaps and resulting inflationary pressures lead to differences in the monetary policy stance. Most of the pairs of currencies in our sample fall into this category. Differences in monetary policy stance, in turn, would lead to differences in the short- and long-run interest rates. When that is the case, investors will take advantage of these small differences and invest in the country

[4] The exchange rates are the Czech koruna (EUR/CZK), the Hungarian forint (EUR/HUF), and the Polish zloty (EUR/PLN). Also they use EUR/USD exchange rate volatility for inter-regional spillovers.

with higher interest rates. This, in turn, will have implications for the exchange rate between the currencies of the two countries. The currency of the country with the higher policy interest rate would be expected to appreciate relative to the country with lower policy interest rates. All of these fit well with the uncovered interest parity hypothesis: Higher interest rates in the home country are consistent with expected future depreciation of its currency.

In the second group of country pairs, the countries differ in terms of basic economic characteristics and their underlying risk characteristics. As a result, the interest rate differentials between the country pairs are permanently higher compared to the country pairs in the first group. While the country pairs in the first group are all industrial countries, in the second group low interest rate industrial countries are coupled with emerging market economies that tend to have much higher interest rates. As the central banks in developed countries switch gears from a tighter to a looser monetary policy stance, there will be plenty of credit available at low cost. Investors take advantage of this opportunity and borrow funds at home to invest in countries with much higher yields. As a result, interest rate differentials play a very important role in determining the direction of the value of currencies relative to others.

Recently, Brunnermeier et al. (2009) have studied how exchange rate dynamics relate to the carry trade positions. Since they focus on carry trade investments across countries, their argument is mostly valid for the second group of country pairs. They argue that the exploitation of the arbitrage opportunities did not lead to rate convergence across countries, because "currency crash risk caused by sudden unwinding of carry trades may discourage speculators from taking on large enough positions to enforce UIP." Large capital flows due to carry trades are possibly associated with destabilizing dynamics in the foreign exchange market, thereby increasing the short-run volatility of the exchange rates. However, when studying volatility dynamics and volatility connectedness across major exchange rates, consideration of carry trade position is of secondary importance. It is observed between chronically low interest rate countries, such as Japan, and higher interest rate countries such as Australia and New Zealand.

When the home country's central bank starts to increase its policy rate, assuming that the foreign central bank in its pair country kept its lower policy rates unchanged, the interest rate differential between the two countries will increase. The resulting capital inflows will lead to an appreciation of the domestic currency. When the central bank's monetary policy stance is clearly understood by the markets, the appreciation of the currency will not necessarily lead to a substantial increase in volatility. However, when markets are unsure about the policy direction (perhaps because the latest data and the official announcements provide little help in forming a clear view about the future policy action), the uncertainty will be high before and after the central bank's decisions and so will be the exchange rate volatility.

6.1.4 Data

We now move to the empirical analysis of volatility connectedness. Our data set includes the exchange rates of the nine major currencies vis-à-vis the U.S. dollar: euro (EUR), British pound (GBP), Swiss franc (CHF), Norwegian krone (NOK), Swedish krona (SEK), Japanese yen (JPY), Australian dollar (AUD), New Zealand dollar (NZD), and Canadian dollar (CAD). Our sample spans from January 1999 to the end of June 2013. Following the approach adopted in Andersen et al. (2001), we drop observations for the fixed and moving official holidays of the United States. In particular, among the fixed holidays we remove Christmas (December 24–25) New Year's (December 31, January 1 and 2) and July 4. In addition, we exclude data for the moving holidays of Martin Luther Day, Presidents' Day, Good Friday, Easter Monday, Memorial Day, Labor Day, Columbus Day, and the Veterans Day.

Our list of moving holidays is longer than that in Andersen et al. (2001) because our inspection of the data shows that there are significant changes in the observed range volatility during Martin Luther Day, Presidents' Day, Columbus Day and Veterans Day. Furthermore, the Securities Industry and Financial Markets Association (SIFMA) recommends that the markets for financial assets denominated in U.S. dollars should be closed during the four additional moving holidays we exclude from our data set. SIFMA's holiday closure recommendations for the United Kingdom and Japan also include all major U.S. holidays. According to BIS (2013), 66% of the global FX trading in 2013 has occurred via the intermediation of dealers in the United Kingdom (41%), the United States (19%), and Japan (5.6%). On a day when there is no or very low FX trading activity in New York, London, and Tokyo, the global activity will also be low. Consequently, we think that it is appropriate to exclude all U.S. holidays from our data set. After removing the observations that coincides with the U.S. holidays, we are left with 3568 daily observations to use from January 4, 1999 to June 28, 2013.

For each currency we calculate Parkinson's daily range volatility estimate $\tilde{\sigma}_P^2$ as described in equation (2.1). In Table 6.2, we provide summary statistics for the annualized range volatilities of exchange rate returns. To be more specific, Table 6.2 includes the first two moments as well as the minimum and maximum values of the annualized daily range standard deviation series for the U.S. dollar exchange rates of the nine major currencies in our sample. Table 6.2 also displays the skewness and kurtosis for the standard deviation of exchange rate returns and its log.

Table 6.2 Descriptive Statistics—Annualized FX Daily Return Volatility (January 1999–June 2013)

	Euro (EUR)	*British Pound (GBP)*	*Swiss Franc (CHF)*	*Norwegian Krone (NOK)*	*Swedish Krona (SEK)*
Mean	11.40	9.87	12.10	13.56	13.77
Median	10.36	8.71	10.93	12.11	12.12
Maximum	54.77	76.97	108.33	77.67	78.31
Minimum	1.88	0.73	1.07	0.34	2.79
Skewness—Vol	1.85	2.96	3.13	2.26	2.13
Kurtosis—Vol	10.29	21.41	33.00	12.83	11.13
Skewness—Log Vol	0.042	0.163	0.097	0.167	0.341
Kurtosis—Log Vol	3.228	3.876	3.613	4.453	3.279

	Japanese Yen (JPY)	*Australian Dollar (AUD)*	*New Zealand Dollar (NZD)*	*Canadian Dollar (CAD)*
Mean	11.49	13.72	15.07	9.53
Median	10.07	11.75	13.09	8.28
Maximum	86.77	127.52	105.40	78.63
Minimum	0.19	1.92	2.53	0.22
Skewness—Vol	2.65	4.12	2.79	2.40
Kurtosis—Vol	17.70	37.35	18.31	15.69
Skewness—Log Vol	0.019	0.498	0.427	–0.363
Kurtosis—Log Vol	4.731	3.886	3.521	4.839

All range volatilities display strong right skewness and they are all strongly leptokurtic. The log range volatilities are closer to a normal distribution. The EUR/USD is the only exchange rate with the log range volatility of returns statistically identical to normal distribution at the 1% level of significance (based on the Jarque-Bera test which is not presented). All other exchange rate return range volatilities are slightly right-skewed (except for Canadian Dollar) and leptokurtic.

Figure 6.1 displays kernel density estimates of the unconditional distributions of the annualized daily range volatilities of exchange rate returns, along with the theoretical normal distribution. The graphs show that the normal distribution is not a poor approximation for the log standard deviation of daily range volatilities for the major exchange rates.

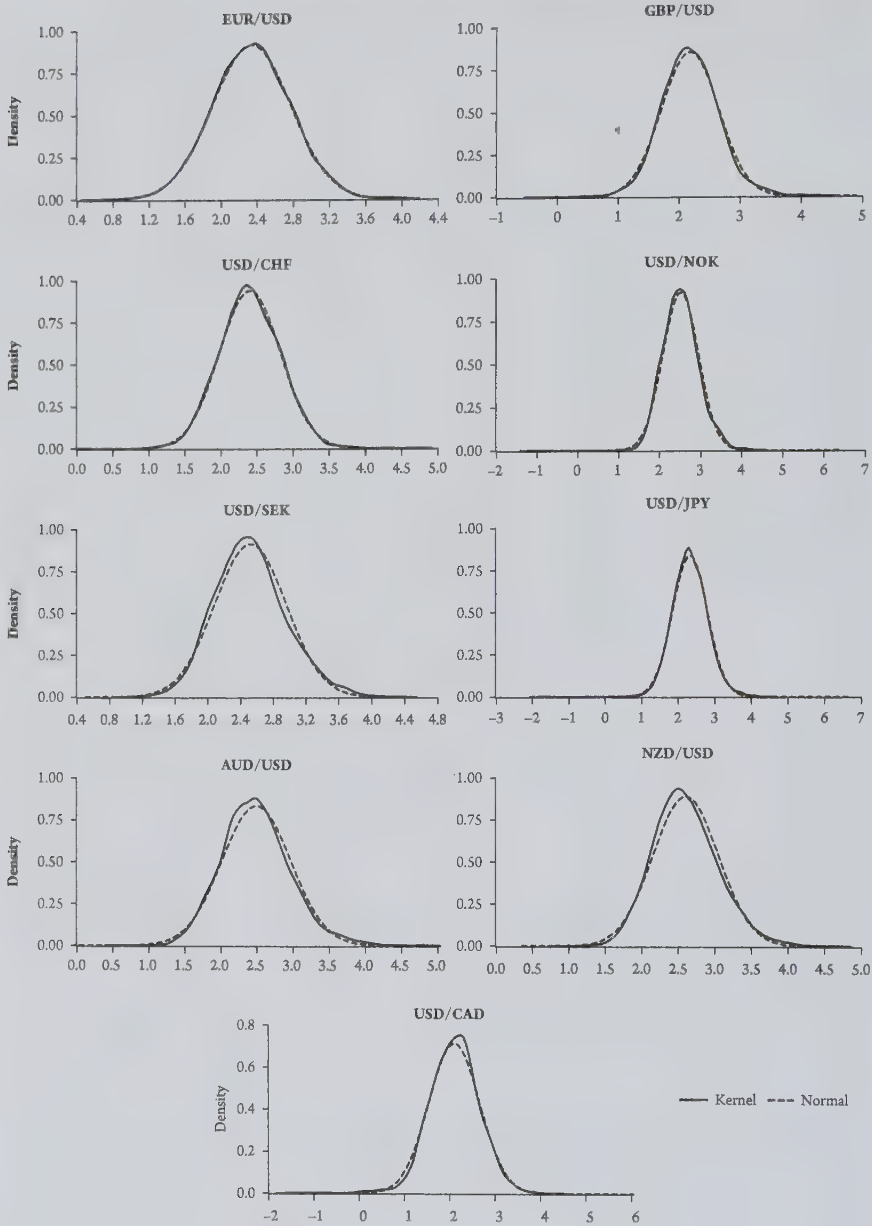


Figure 6.1 Log range FX volatility–kernel density estimates.

6.2 FULL-SAMPLE VOLATILITY CONNECTEDNESS

Table 6.3 displays the full-sample pairwise and total directional volatility connectedness measures for the global FX markets along with their bootstrapped standard errors. It is apparent in the table that all pairwise connectedness measures are statistically significant at the 1% level.

Table 6.3 Volatility Connectedness Table, USD Exchange Rates of Nine Major Currencies

	EUR	*GBP*	*CHF*	*NOK*	*SEK*	*JPY*	*AUD*	*NZD*	*CAD*	*FROM*
EUR	27.6	7.9	16.9	14.7	15.7	2.9	8.0	4.5	1.9	72.4
GBP	10.2	35.9	7.9	10.6	9.9	3.4	9.0	7.3	5.8	64.1
CHF	20.7	7.5	31.3	12.2	12.0	3.7	6.2	3.9	2.4	68.7
NOK	14.9	7.8	10.1	28.8	15.9	2.7	8.8	6.0	5.1	71.2
SEK	15.8	7.6	9.9	16.1	29.1	2.9	9.1	5.6	3.8	70.9
JPY	6.4	5.2	6.3	6.2	5.9	53.6	8.1	5.9	2.3	46.4
AUD	8.0	6.4	5.0	9.3	8.7	5.0	34.2	17.2	6.0	65.8
NZD	6.2	6.6	4.1	8.4	7.6	4.5	21.8	36.1	4.7	63.9
CAD	2.9	7.8	2.9	8.9	5.4	2.0	9.4	6.6	54.1	45.9
TO	85.1	56.9	63.1	86.4	81.1	27.0	80.5	57.0	32.1	
NET	12.7	−7.2	−5.5	15.2	10.2	−19.5	14.7	−6.8	−13.8	**63.2**

Notes: The sample is January 4, 1999 through June 28, 2013. All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in this chapter's appendix, in Table 6.A.1.

Let us now focus on some of the interesting facts that emerge from Table 6.3. As can be seen from the right bottom corner cell of the table, with a value of 63.2%, the total volatility connectedness of the major exchange rates is significantly higher than the volatility connectedness among the global stock (41%) and bond (53.7%) markets we reported in Chapters 4 and 5. It is therefore important to note that the number of variables in the FX market VAR model is nine, one less than the number of variables in the stock and bond markets. As we have already noted several times in previous chapters, the connectedness measure is an increasing function of the number of variables in the system. Therefore, the exchange rates are more connected than the global stock and bond markets.

Second, the total "from" and "to" connectedness measures (see "FROM" column and "TO" row) are distributed tightly across countries compared to other asset classes we have analyzed thus far. While the "to" connectedness varies between 27% and 86.4% (a range of 59.4 percentage points), the "from" connectedness varies between 45.9% and 72.4% (a range of 26.5 percentage points). A comparison of the survivor function plots in Figure 6.2 with the corresponding plots in Figure 4.2 shows how tightly the "to" and, especially, the "from" connectedness are distributed in the case of global FX markets compared to that of stock markets.

We think that these results reflect several important differences between the global FX markets, on the one hand, and the global stock and bond markets, on the other.

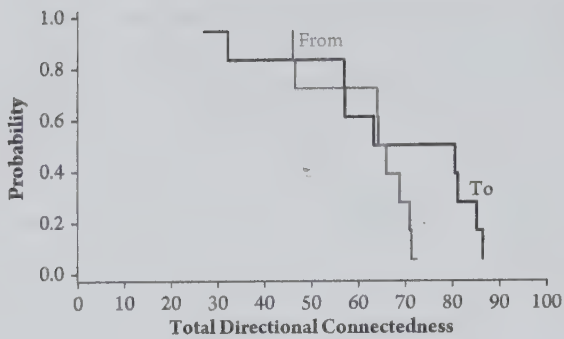


Figure 6.2 Full-sample empirical survivor functions—FX volatility connectedness.
We plot the empirical survivor functions for total directional connectedness "to others" ("to" connectedness) and "from others" ("from" connectedness). The predictive horizon for the underlying variance decomposition is 12 days.

As we have already discussed above, the foreign exchange markets in major financial centers around the world are more integrated compared to stock and bond markets to form a truly global FX market. Furthermore, the daily turnover in the global FX markets is $5.3 trillion, a multiple of the turnover in the global bond and stock markets. Second, in the FX market major currencies are traded as closely substitutable assets, compared to stocks or bonds from different countries. In addition, exchange rates of the nine major currencies in our sample are defined relative to the U.S. dollar. When there is macroeconomic news or policy announcements that may affect the value of the U.S. dollar relative to other currencies, all exchange rates in our sample will be subject to the shock one way or the other. As a result, when there is a volatility shock to one exchange rate, it is highly likely to be quickly transmitted to other exchange rates.

A tighter distribution for the "from" connectedness over the mid-range is consistent with the fact that the nine major currencies in our sample are all tightly connected so that each currency is open to the spillovers of volatility shocks from other currencies. The fact that the "to" connectedness is more dispersed than the "from" connectedness, on the other hand, shows the differences across currencies in spreading volatility shocks to other major currencies. As we have already seen in the methodology part of the book, the total volatility "to" connectedness of an asset can be high, for either it is a very central asset among its peers with high market turnover and capitalization or it has been subject to frequent volatility shocks over the full sample, or both.

In order to see the differences among the exchange rates, let us take a closer look at their various connectedness measures. The Norwegian krone–dollar exchange rate has the highest "to" and "net" connectedness (86.4% and 15.2%, respectively). The euro-dollar exchange rate has the highest "from" connectedness (72.4%). After the krone–dollar exchange rate, the U.S. dollar exchange rates of the euro (85.1%), the Swedish krona (81.1%), and the Australian dollar (80.5%) have the highest volatility "to" connectedness with other exchange rates. Interestingly, the dollar–yen (USD/JPY) exchange rate has the lowest "to" connectedness (27%). Its "from" connectedness is 46.4%, the second lowest after the USD/CAD. With a "net" connectedness of –19.5%, USD/JPY is the exchange rate whose daily return volatility is substantially driven by volatility shocks to other exchange rates. USD/CAD has the lowest "from" connectedness (45.9%) and the second lowest "to" connectedness (32.1%). With a value of –13.8%, USD/CAD has the second lowest "net" connectedness after the USD/JPY exchange rate.

Another interesting fact that emerges in the full-sample analysis is the regional clustering of the pairwise volatility connectedness. Five European currencies form a regional cluster with higher pairwise connectedness among each other compared to their connectedness with the currencies outside the region. More than two-thirds of the "from" connectedness of the exchange rates of the European currencies is contributed by other European currencies. A similar observation is valid for the "to" connectedness of the European currencies. To mention one, the euro's pairwise "to" volatility connectedness with the other four European currencies (British pound, Swiss franc, Norwegian krone and Swedish krona) accounts for approximately three-quarters of its total "to" volatility connectedness.

The highest pairwise connectedness is observed from AUD/USD to NZD/USD is (21.8%), followed by the connectedness from EUR/USD to USD/CHF (20.7%). Both indicate that there may be regional clustering in volatility connectedness among the major exchange rates. The connectedness from NZD/USD to AUD/USD and from USD/CHF to EUR/USD are also high (17.2% and 16.9%, respectively).

Even though among the countries represented in our sample Japan is geographically the country closest to Australia and New Zealand, its pairwise connectedness measures with the two countries are low. While Japanese yen does not seem to be part of the Asia-Pacific regional cluster in exchange rates, all European currencies in our sample are part of the European cluster. Pairwise connectedness measures for the other European exchange rates (USD/SEK, USD/NOK, and GBP/USD) with the EUR/USD exchange rate are high, all ranging between 10% and 20%.

The Canadian dollar, on the other hand, has its highest pairwise "to" and "from" connectedness with the Australian dollar. The relatively high pairwise connectedness of the two currencies is most likely due to the high commodity export dependence of the Canadian and Australian economies. When there are shocks in the commodity markets, the volatility of the two currencies is likely to be affected. Reflecting this fact, they have been classified as "commodity currencies" since the early 2000s by the World Bank and the IMF. Even though the New Zealand dollar is also another commodity currency, its volatility connectedness with the Canadian dollar is weaker than that of the Australian dollar.

6.3 DYNAMICS OF VOLATILITY CONNECTEDNESS

After conducting the full-sample static volatility connectedness analysis of major exchange rates, we now turn to the analysis of dynamic volatility connectedness obtained through rolling-sample windows. We start with the analysis of the total connectedness and then move to the total directional connectedness before closing the section with the analysis of pairwise connectedness.

6.3.1 Total Volatility Connectedness

Figure 6.3 presents the total volatility connectedness over the rolling 100-day windows throughout the January 1999 to June 2013 period.

Having covered the volatility connectedness in the global stock and bond markets, we can discern how different the rolling total volatility connectedness plot for the FX markets looks from those for the global stock and bond markets. For one, despite many economic policy shocks or financial market shocks, the upward trend in the FX market total volatility connectedness is milder than that of the global stock and bond markets. At its lowest point in July 1999, the total connectedness index was 47%. The local minimum point the index attained 14 years later in May 2013 was 51%. Yes, there are many instances of sharp increases in the index, yet as the data covering the high-volatility periods are dropped from the sample window, the index always returns to the 50%–60% range.

The second striking difference lies in the appearance of major and minor cycles in the connectedness plot. In the case of global stock and bond markets, the total connectedness went through two large cycles around the tech-bubble burst of 2000 through 2002 and during the global financial crisis from 2007 through 2009. In between, from 2003 to 2006, both the stock and bond markets experienced shorter,

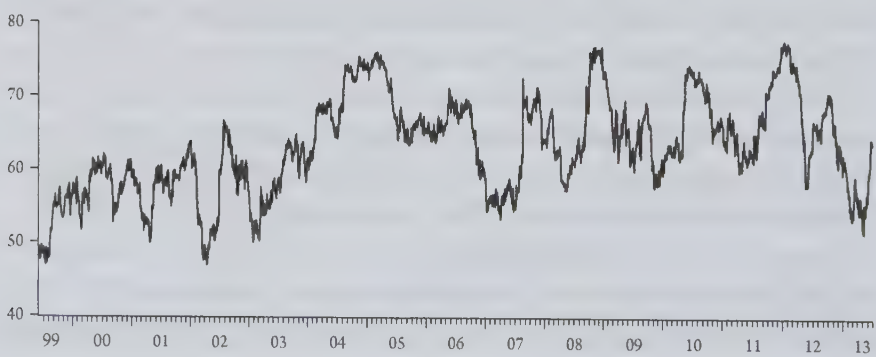


Figure 6.3 Total FX market volatility connectedness—9 major currencies vis-à-vis USD (100-day window).

minor cycles of volatility connectedness (see Figures 4.3(b) and 5.5). In the case of the global FX markets, the timing of the major and minor cycles is reversed. From 1999 through 2003 and from 2007 through 2010, the volatility connectedness went through shorter, minor cycles, rather than longer, major cycles. In between, from 2003 to 2007, the global FX markets experienced a rather long-lasting major cycle in volatility connectedness.

Among other things, the time trajectory of connectedness is conditioned by such things as the interest rate decisions of the central banks in different countries, FX market interventions by the central banks, and unexpected shocks to financial markets, such as the Lehman Brothers bankruptcy of September 2008, that lead to a sudden increase in the volatility of the exchange rate return.

The Federal Reserve's policy decisions and the market participants' expectations of these decisions had great influence on the USD exchange rates of major currencies. The first major volatility connectedness cycle lasted from mid-1999 until the end of 2000. The period up to the middle of 2000 was marked by a contractionary monetary policy stance. As the FOMC increased the federal funds target rate from 4.75% at the end of 1998 to 6.5% in May 2000, starting in 1999 through the end of 2000 the U.S. dollar appreciated against all other major currencies. However, following the tech-bubble burst, the FOMC reversed its policy stance and steadily cut the Fed funds target rate throughout 2001 all the way down to 1.75%. The sharp reversal in monetary policy also led to a reversal in the fortunes of the U.S. dollar vis-à-vis other currencies. The depreciation of the U.S. dollar continued steadily until the climax of the global financial crisis in October 2008.

During this period the euro also contributed significantly to the volatility in FX markets. The euro was introduced in 1999 as the official currency of the member countries of the newly formed European Monetary Union, which is also called the eurozone. Even though it was expected to be a strong currency as the replacement of the Deutsche mark, the euro's movements were very erratic in the first couple of years of its existence. For example, the annualized daily volatility of the EUR/USD rate in 2000 was higher than the volatility of other currencies' USD exchange rates (except for USD/SEK and NZD/USD). Immediately after its introduction, the euro started depreciating against the dollar. From January 1, 1999 to September 22, 2000, it lost 29% of its value against the U.S. dollar. The rapid depreciation of the euro against the U.S. dollar, combined with the oil price hikes, led the euro prices of oil to reach unbearable levels for the European member countries. Social unrest further increased the volatility of the euro. In response, the central banks in the United States, Britain, Europe, and Japan undertook a coordinated intervention on September 22, 2000. On the same day, the United States started selling oil from its emergency oil stocks. Over this period, it was not only the EUR/USD that was volatile, but the U.S. dollar exchange rates of other European currencies (USD/CHF, USD/SEK, USD/NOK, except for the GBP/USD, perhaps) were also highly volatile.

Faced with the threat of a major recession following the tech-bubble burst and the ongoing decline in the stock market, U.S. monetary policy switched gears toward a strong expansionary stance in early 2001. In its first five meetings of 2001, the FOMC cut the Fed funds target rate 50 basis points each, bringing it down from 6.5% at the end of 2000 to 4% in May 15. With this round of aggressive cuts, the U.S. dollar's depreciation started to gain momentum. From February to the end of April, the volatility connectedness gradually increased by three percentage points. In the two weeks before the FOMC's May 15 meeting, the volatility connectedness jumped by another four percentage points, marking the beginning of the short cycle in 2001. However, as the FOMC insisted on its aggressive policy stance, the volatility of the U.S. dollar exchange rates continued to increase in the second half of the year and so did the total volatility connectedness. Combined with the uncertainty after the 9/11 terrorist attacks, the volatility connectedness reached 64% by the end of 2001, a 14-percentage-point increase from April to the end of 2001.

The third upward move in the volatility connectedness was experienced in mid-2002. Despite the aggressive rate cuts throughout 2001, the devastating impact of the tech-bubble burst followed by the corporate governance failures in large American corporations such as Enron and WorldCom/MCI and the uncertainty after the terrorist attacks of 9/11 all kept stock market volatility high in the United States. We have already discussed the importance of the Enron and MCI/WorldCom scandals for the volatility of bank stock returns and the volatility of stock market index returns in Chapters 3 and 4, respectively. FX markets could not be insulated from the impact of the corporate scandals in the United States. As a result, from the beginning of April to the end of July 2002, the volatility connectedness in FX markets increased from 47% to 67%.

The Iraq war proved to be another source of uncertainty, and its short-lived impact on exchange rate volatility was felt in the first quarter of 2003. After months of debates, controversies, and preparations, the invasion of Iraq by the United States and coalition forces started on March 20, 2003, and the volatility connectedness jumped close to four percentage points. As the coalition forces succeeded in taking control of the country very quickly, the volatility in FX markets and the resultant volatility connectedness subsided quickly and was down to 52% by mid-May 2003.

The exchange rate volatility connectedness started to increase in mid-2003 again. This time the upward movement in the connectedness continued until the second half of 2005. Starting from 50% in March 2003, it reached 76% by March 2005. As it started declining again, it dropped to only 64% in July 2005. The connectedness index fluctuated around 65% for close to a year. After a brief upward movement following the

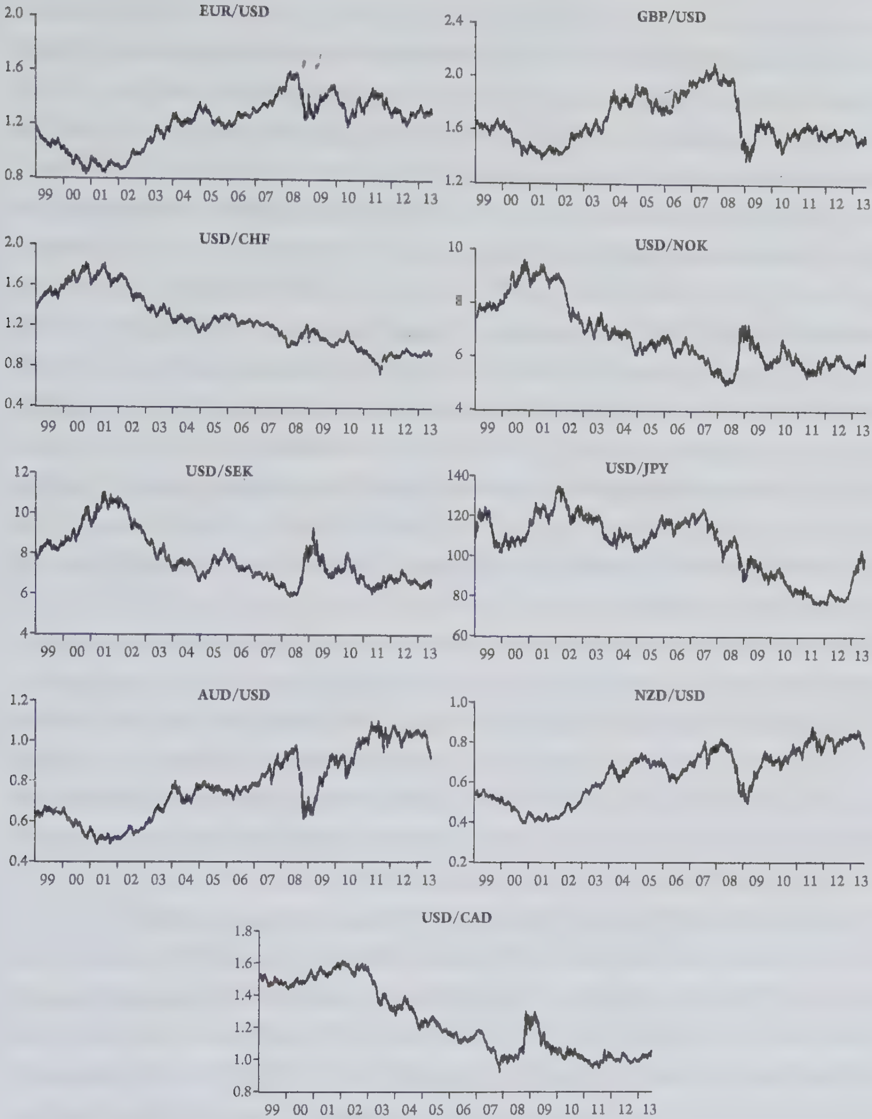


Figure 6.4 Exchange rates of major currencies vis-à-vis the U.S. dollar.

Fed's policy rate decision in mid-2006, total volatility connectedness declined rather quickly to 54% by January 2007.

The period from mid-2003 to mid-2005 can be described as a period of zig-zags in the U.S. dollar's value against other major currencies (see Figure 6.4). In mid-2003 the U.S. economy was still not out of the low-growth period, and the fear of deflation was still lingering in the markets. In the meantime, its counterpart on the other side of the Atlantic, the ECB, lowered its policy rate from 2.75% at the end of 2002 to 2.0% by June 2003. Worried about the deflationary threat, at its June 2003 meeting the FOMC lowered the federal funds' target rate from 1.25% to 1%, the lowest rate up to that point. After the respective rate decisions of the two central banks, the difference between the eurozone and the U.S. short-term interest rates declined from 1.5 percentage points at the end of 2002 to one percentage point at the end of June 2003. As a result of the decline in the difference between the two countries' interest rates, the U.S. dollar appreciated against the euro and other currencies for a couple of months.

In the meantime, the U.S. current account deficit continued to widen. In response, at their September 2003 meeting the G8 finance ministers called for more flexibility in exchange rates. With their statement, finance ministers intended to call their Chinese and East Asian counterparts to allow their currencies to fluctuate more freely rather than fixing to the dollar. While the East Asian countries did not change their exchange rate policy stance, the statement in effect initiated a speedy depreciation of the U.S. dollar against the major currencies. The increased exchange rate volatility led to higher volatility connectedness. From a low of 55% on May 22, 2003, the volatility connectedness in FX markets increased steadily in the second half of 2003 to reach 68% by the end of February 2004.

After leaving its policy rate intact for a year, the FOMC gradually changed its policy stance in the second half of 2004 in response to the accelerating pace of the economy. At each of its five meetings in the second half of 2004, the FOMC increased the Fed funds target rate by 25 basis points. With the December 2004 rate hike, the U.S. short-term policy rate closed the year at 2.25%, 25 basis points above the ECB's policy interest rate. During this period, the volatility connectedness increased from 65% (end of June 2004) to 76% (end of February 2005).

In 2005, the Federal Reserve continued with its gradual tightening of monetary policy. At eight of its 11 meetings in 2005, the FOMC increased the Fed funds target rate uniformly by 25 basis points. As a result, the policy interest rate increased gradually from 2.25% at the beginning of the year to reach 4.25% at the end of 2005. While the Federal Reserve increased its policy rate eight times in 2005, the ECB increased its policy rate only once, in December 2005. As a result, the U.S. policy rate was higher than that of the eurozone for most of 2005.

The volatility connectedness fluctuated around 75% in the first four months of 2005. However, once the investors were convinced about the direction of monetary policy, the tighter monetary policy showed its effect. The U.S. dollar started to appreciate against all currencies, and this became the main trend in 2005. With an appreciating dollar, the volatility and its connectedness in FX markets declined. At the beginning of July 2005, the volatility connectedness was down to 64%.

From July 2005 to May 2006, the volatility connectedness fluctuated around 65%. Faced with the threat of inflation, the FOMC continued to increase its policy rate in 2006. Driven by an expanding demand in the United States, the world economy started to grow faster in 2006. The ECB also changed its policy stance and increased its policy rate at its March and June meetings by a total of 75 basis points. Central banks around the world had to switch to tighter monetary policy, which led to the reversal of the U.S. dollar's fortunes relative to those of other currencies.

The FOMC meeting on May 10, 2006 was of critical importance. After increasing the Fed funds target rate by 25 basis points at its January 31st and March 28th meetings, the FOMC decided to increase the target rate at its May 10 meeting, with an announcement that it might repeat its rate hike decision at its June 30 meeting. The markets were caught off guard. This was mostly an unanticipated policy move. As the federal funds target rate was already at a high level, 5.25%, the majority of market participants were expecting no further rate hikes.

The FOMC's decision and announcement led to a temporary increase in the volatility of major exchange rates. However, its most important effect was on emerging market economies and their currencies. As the Fed funds target rate moved higher, U.S.-dollar-financed carry trades in emerging markets became less attractive. As a result, the policy decision convinced investors to close their carry trade positions. Following this decision, the stock, bond, and currency markets in many emerging market economies suffered substantially. We have already discussed the effects of the FOMC's decision on the volatility connectedness across the global stock and bond markets in Chapters 4 and 5, respectively. Unlike the case in stock markets, the impact of the FOMC's decision on the volatility connectedness across the major exchange rates was limited and temporary. As a result, the connectedness index jumped from 66% on May 9 to 71% on May 22, before declining to 54% by January 2007.

Following the long cycle that lasted from mid-2003 to mid-2007, the volatility connectedness in FX markets went through five shorter major cycles from mid-2007 through the end of 2010. Each of these short connectedness cycles had higher altitude compared to the three short cycles of the 1999–2002 period. With the liquidity crisis of August 2007, global FX market volatility and, hence, volatility connectedness increased again. Actually, in one month from July 5 to August 20, the volatility connectedness had its biggest jump (17 percentage points). It increased one more time in September 2008, following the rescue operation for Fannie Mae and Freddie Mac and the collapse of Lehman Brothers. This time it increased from 63% at the end of August 2008 to 77% at the end of October 2008. As the financial crisis lost its steam toward the end of the first half of 2009 and following the positive results of the stress tests applied to American banks, the total connectedness index declined all the way down to 60% by mid-2009. Following the EU's inability to resolve the Greek debt crisis, FX market volatility connectedness increased 12 percentage points in May 2010. The FX market volatility connectedness increased again in the summer of 2011, following the spread of the euro sovereign debt crisis to Spain and Italy; furthermore, the worsening of the Spanish banking crisis and the Greek elections increased the tensions in the FX markets, generating another significant jump in the total volatility connectedness. Mario Draghi, the President of the ECB, in his policy statement in late July in which he bluntly indicated that the ECB was ready to do whatever it tåkes to support the euro, was critical in holding the situation under control in the rest of 2012.

The total connectedness declined swiftly from 70% in late 2012 to 52% in early May 2013. However, the Fed's announcement that it would start tapering its quantitative easing policy in the second half of 2013, with further tightening in 2014, affected FX markets significantly. From May 22 onward, the volatility connectedness increased from 52% to 64% by the end of June.

As we noted at the beginning of this section, the dynamics of the FX market volatility connectedness was substantially different from the ones observed in the global bond and stock markets. This is perhaps an outcome of the fact that while bond and stock market volatilities are countercyclical, FX market volatility is not closely linked with the business cycle. For example, during the 1999–2002 period, which is marked by the U.S. recession, the FX market volatility connectedness followed short cycles. In contrast, during the period of robust growth from the second half of 2003 through the first half of 2005, it followed an upward trend. Even though the connectedness index declined after the mid-2005, it stayed high, above 60%, until the end of 2006. The increased exchange rate volatility and volatility connectedness during this period was mainly due to the lack of synchronization between the U.S. and the European business cycles and the increase in the short-term policy interest rate differential between the two sides of the Atlantic. During the global financial crisis and the subsequent global recession, the short cycles of FX market volatility connectedness were observed again.

When we compare the total connectedness index based on the 200-day rolling-sample window in Figure 6.5 with the one obtained from a 100-day rolling-sample

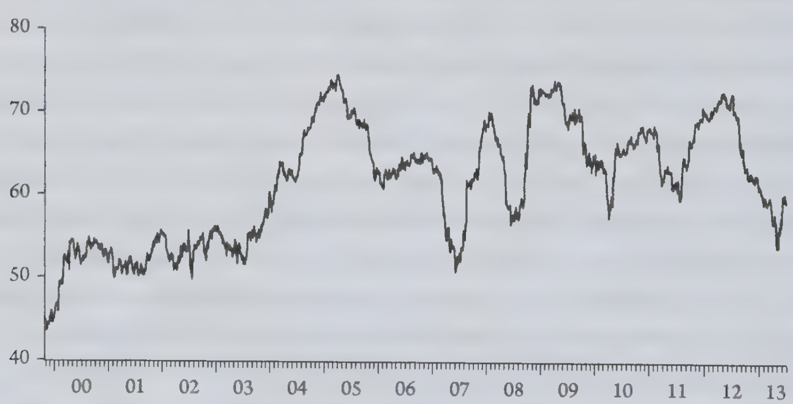


Figure 6.5 Total FX market volatility connectedness—9 major currencies vis-à-vis USD (200-day window).

window in Figure 6.3, the upward trend that lasted from 1999 to 2005 can be easily observed, as well as the turning points in 2005 through the end of the sample. Overall, the results are robust to the choice of window size. Yet, there are some differences, as expected. As the 200-day window includes more observations, the altitude of the cycles tends to be smaller. Furthermore, the upward and downward moves in the index tend to be smoother.

6.3.2 Total Directional Volatility Connectedness

Our analysis of the rolling total connectedness plot prepared the ground for the analysis of more disaggregated forms of connectedness. Next, we discuss the dynamics of total directional volatility connectedness for each currency. Figure 6.6 displays how the total directional ("to", "from", and "net") connectedness for the nine exchange rates changed over time. Let us first start with some general observations.

As was the case in the global stock and bond markets, the "from" connectedness plots for all currencies are smoother than the corresponding "to" connectedness plots. When there is a volatility shock to any one of the nine exchange rates, this shock is transmitted to other currencies. The "to" connectedness takes full account of the shock and its transmission. As the size of the shocks may vary from day to day, it is quite normal for the "to" connectedness index to vary over time. Because the transmitted shock is distributed among the eight other currencies, even though the original volatility shock itself is large, its contribution to the "from" connectedness of each of the other currencies can be smaller.

Furthermore, the "from" connectedness plots of the European currencies, with the exception of the British pound, are much smoother than the "from" connectedness plots for other currencies. As we will see when we discuss the pairwise connectedness below, these currencies traded much more with each other and therefore are not influenced much from shocks to other exchange rates. As the United Kingdom has had stronger historical and economic ties with Australia, New Zealand, and Canada, the GBP/USD exchange rate is likely to be more affected from shocks to the AUD/USD, NZD/USD, and USD/CAD. That is why its "from" connectedness is not as smooth over time as the ones for the continental European countries.

After these observations, we can now focus on the "to" and "from" connectedness of each currency separately. Let us start with the EUR/USD exchange rate. With the third lowest mean return volatility, after the USD/CAD and GBP/USD exchange rates, it is definitely not the most volatile exchange rate. Yet, in the full sample, it has the highest volatility connectedness among the nine exchange rates we consider. Its volatility connectedness stays high throughout the sample in the rolling connectedness plots. Its "to" connectedness starts around 80% in 1999 and increases to around

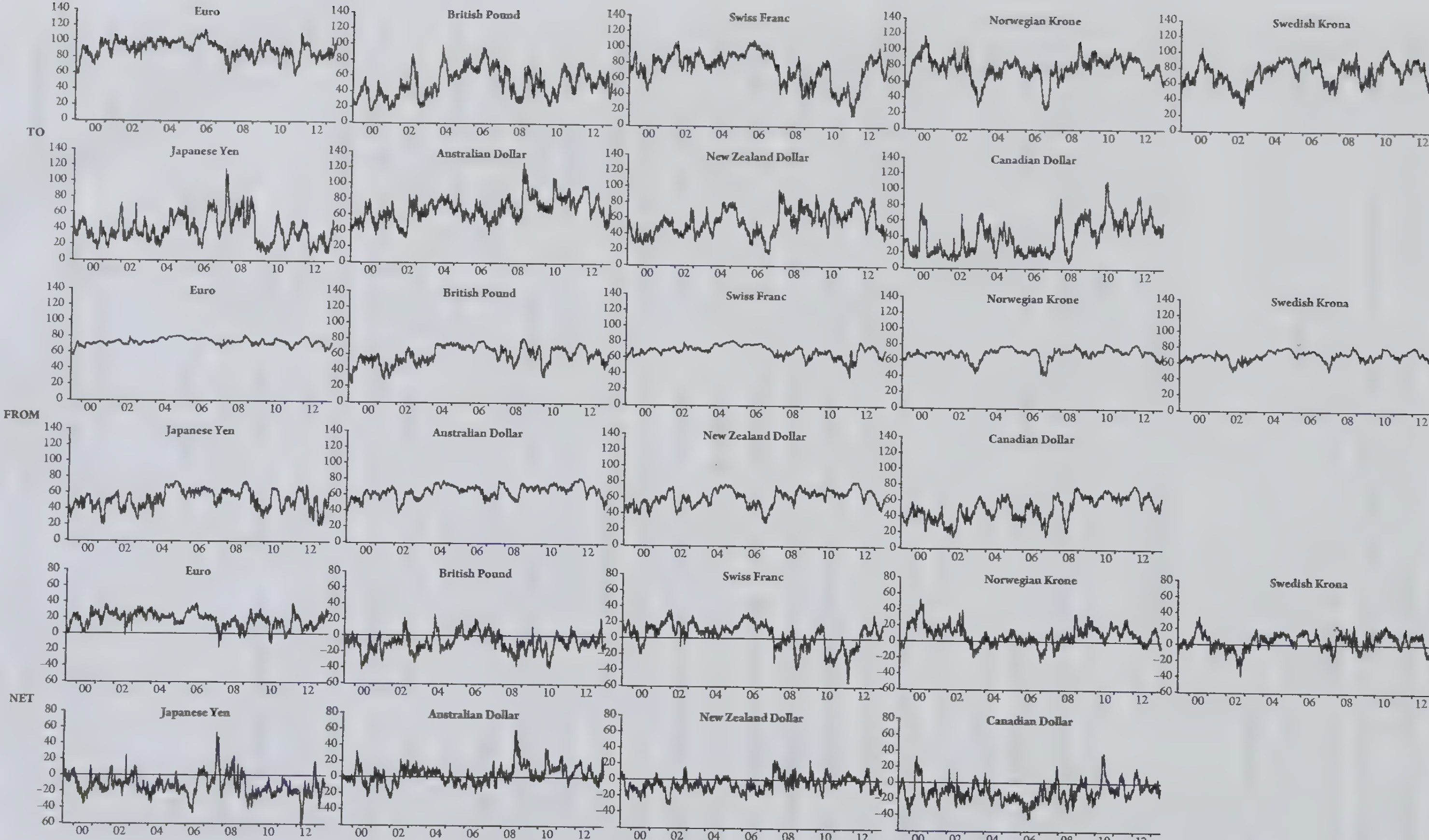


Figure 6.6 Total directional volatility connectedness—FX market (100-day window).

120% by 2006. Its "from" connectedness is also high, fluctuating between 60% and 80%. The difference between the two measures results in a "net" connectedness for the euro that fluctuated around 20% until the global financial crisis. As other currencies became more connected during the crisis, the connectedness of the euro declined slightly. The EUR/USD exchange rate has high connectedness throughout the whole sample, because both the U.S. dollar and the euro are the top two vehicle currencies around the world. Any change or fluctuation in the EUR/USD exchange rate is watched very closely around the world.

A closer look at the "to" connectedness plots in Figure 6.6 helps us see that all major European currencies, including the euro, contributed to the upward cycle of 1999. During the brief upward move in September 2000, however, the EUR/USD exchange rate was the one that contributed the most, along with the Japanese yen, whose "to" connectedness increased for a short period of time only.[5]

The euro's contribution to the connectedness continued to be high throughout the 1999–2013 period, but it did not fluctuate substantially over time. The "to" connectedness of the British pound, on the other hand, fluctuated substantially over time. The British pound contributed substantially to the increase in connectedness throughout 2001 and 2002. While the GBP/USD exchange rate had risen from 1.4 to 1.6 in 2002, its "to" volatility connectedness increased from 20% to 80%. Compared to the British pound, the "to" connectedness of the euro and the Swiss franc fluctuated very little in both instances.

After a sharp decline at the end of 2002, the "to" connectedness of the British pound surged even further in late 2003 and early 2004. As a result, the "net" connectedness of the GBP/USD exchange rate moved into the positive territory for the first time in the sample. The latest move in the GBP/USD exchange rate was a result of the short-term policy rate differentials between the United States and the United Kingdom. Similar to the Federal Reserve and the ECB, the Bank of England's Monetary Policy Committee continued to implement an expansionary policy in 2003. It lowered the policy rate by 50 basis points at its February and July 2003 meetings. However, the Bank of England switched from an expansionary to a contractionary policy stance earlier than the other two central banks, when it decided to increase the policy interest rate at its November 2003 meeting. The MPC did not change the policy interest rate at its December 2003 and January 2004 meetings. However, as inflationary pressure started to increase, the MPC increased the policy interest rate by 25 basis points in February, May, June, and August 2003. As a result, the policy interest rate reached 4.75% by August 2004. As the interest rates increased, the British pound started to appreciate against the U.S. dollar

[5] Actually, as we will discuss later, among all the currencies, the Japanese yen is the only currency whose "to" connectedness displays frequent spikes. We think this is a reflection of the frequent FX market interventions by the Bank of Japan.

and other currencies. At the same time, the GBP/USD exchange rate daily return volatility increased substantially in 2004, leading to a substantial rise in the "to" connectedness of the GBP/USD exchange rate, which as a result surpassed the 100% mark.

Even though the "to" connectedness of the British pound declined after the 2004 episode, it continued to be around 80% in 2005 and 2006. It declined further to the 20%–40% range as the first stage of the global financial crisis unfolded in 2007 and early 2008. However, with the collapse of Lehman Brothers, the "to" connectedness of the GBP/USD exchange rate increased to 80% in late 2008 and early 2009. Declining in the second half of 2009, the "to" connectedness of the GBP/USD increased again throughout 2010 as a result of the uncertainty generated by the eurozone debt crisis.

The "to" connectedness of the Swiss franc was quite high earlier in the sample as well. Starting around 80% in 2000, its connectedness to others increased, surpassing 100% in 2006. Its "net" connectedness was positive between 1999 and 2006, even though it was not as high as that of the euro. Once the U.S. financial crisis started in 2007, its "to" and "net" connectedness declined sharply, to 50%, in the second half of 2007. This was a period when all major exchange rates vis-à-vis the U.S. dollar became highly volatile. As a result, the Swiss franc was seen as a safe haven. As more and more investors decided to hold the Swiss franc, the volatility of the Swiss franc declined and so did its "to" connectedness. However, due to substantial losses incurred by Swiss banks, there was a temporary reversal of the downward trend from the end of 2007 through the first quarter of 2008.[6] With the collapse of Lehman Brothers, the downward trend in the Swiss franc's connectedness resumed, dropping to less than 40%.

Once the markets saw the light at the end of the tunnel in March 2009, the U.S. dollar started to depreciate quite rapidly. During this period, the "to" connectedness of the Swiss franc increased once again. It more than doubled from the beginning to the end of 2009. In December 2009, the Greek debt crisis started to dominate the news in Europe and around the world. As European leaders showed great reluctance to resolve the crisis, the markets became jittery and the euro started depreciating against the dollar in early 2010. Worries about the Swiss banks and the impact of an EU-wide recession on Switzerland led to the depreciation of the Swiss franc against the dollar. During this period, the "to" volatility connectedness of the USD/CHF diminished rapidly from 86% to 25%.

While the "to" connectedness of the Swiss franc (USD/CHF) declined during the 2007–2009 global financial crisis, the "to" connectedness of the commodity currencies increased sharply during the crisis. These exchange rates had lower connectedness to start with but had become more important volatility connectors after 2007. Even

[6] As of April 2008, UBS and Credit Suisse, two major Swiss banks, had written down $37 billion in losses due to the U.S. subprime crisis.

though these currencies were affected by the global financial crisis, an important part of their action was due to being very closely linked to the commodity markets. When there were some encouraging signs in the second and third quarters of 2008 that the U.S. financial crisis might be contained, the commodity markets went through a short-term boom, mostly driven by the robust growth in China and other emerging market economies. However, given the impact of the U.S. financial crisis on the real economy in the United States and Europe, the markets were not completely out of the woods. During this period, intra-day volatility in the commodity markets was high (see Figure 2.1(c)). The increased volatility in the commodity markets meant that the currencies of the commodity-exporting countries were appreciating while at the same time they were becoming more volatile. As a result, we observe that the volatility connectedness of these currencies increased substantially in 2008 and after.

As the Japanese yen is one of the most traded currencies against the U.S. dollar, we next analyze the "to" connectedness of the USD/JPY exchange rate. The "to" connectedness of the USD/JPY exchange rate differs from others, in that its upward jumps are short-lived most of the time. These jumps are mostly spikes that lasted shorter than the sample window length of 100 days. Its "to" connectedness spiked after the concerted central bank interventions in September 2000 and then in May 2001. Even during the liquidity crisis of August 2007, the "to" connectedness of the USD/JPY jumped by 80 points and came down within two months. We think that the main factor behind the short-lived spikes in the "to" connectedness of the USD/JPY is the Bank of Japan's policy of frequent FX market interventions. Unlike other central banks, the Bank of Japan prefers to intervene in FX markets when deemed necessary, without the cooperation of other central banks. Most of the time, this policy resulted in significant jumps in the "to" connectedness of the exchange rate.

Other exchange rates, such as the AUD/USD, USD/NOK, USD/SEK, and NZD/USD also have high volatility connectedness in the full sample and in rolling sub-sample windows, even though they are not as central as the EUR/USD rate. The high-volatility connectedness of these currencies is mostly with the currencies in their regional cluster and/or conditioned by other factors such as the commodity price shocks of 2008.

The "to" connectedness of the AUD/USD exchange rate was low to begin with: As of 1999, it fluctuated between 35% and 60%. However, it contributed to the jump in the total connectedness index at the beginning of 2000. At the time, the volatility of the AUD/USD exchange rate increased significantly. On January 28, 2000, for example, the volatility jumped from 18% on the previous day to 36%. In the meantime, its "to" connectedness increased from 36% at the end of 1999 to 78% by mid-March.

The "to" connectedness of the AUD/USD exchange rate increased gradually in late 2000 and early 2001, followed by a minor jump in mid-2001 and a major jump in mid-2002. It recorded a 40-percentage-point increase in early 2003, along with the British pound and the New Zealand dollar. The increase in the "to" connectedness of the AUD/USD exchange rate was much less pronounced compared to that of GBP/USD and NZD/USD. After the increase, the "to" connectedness of AUD/USD stayed in the 60%–80% band for some time. With the liquidity crisis of 2007 the "to" connectedness of the AUD/USD jumped by 40 percentage points, followed by a 100-percentage-point jump in late 2008, after the collapse of Lehman Brothers. Even though the "to" connectedness of the AUD/USD exchange rate declined again in 2009, it fluctuated in the 60%–80% band, without going back to the lower levels it had attained earlier in the sample.

Australia and New Zealand are tightly integrated economies. The structures of the two economies are not much different either. In that regard, one would expect that the "to" connectedness of the AUD/USD and NZD/USD exchange rates to follow quite similar paths. But that is not the case: The "to" connectedness of the NZD/USD exchange rate followed a path quite different from that of the AUD/USD exchange rate. While the upward movements of the "to" connectedness of the NZD/USD exchange rate are more pronounced, those of the AUD/USD exchange rate are mostly modest. This is apparent in the upward movements of NZD/USD's "to" connectedness in 2001, at the end of 2002, in 2003–2004, and in 2007. The only exception, obviously, is the meteoric rise in the "to" connectedness of the AUD/USD after the collapse of Lehman Brothers in 2008. The dynamic connectedness of the two exchange rates diverged in 2009 as well. While the "to" connectedness of the AUD/USD was declining gradually, that of the NZD/USD moved up.[7]

6.3.3 Pairwise Directional Connectedness

In this section we analyze the dynamics of pairwise directional connectedness, which is visually depicted in the matrix of pairwise directional connectedness plots in Figure 6.7. Given that there are too many pairwise plots in the matrix, it is not possible for us to analyze each pairwise connectedness plot in detail. We therefore focus on common trends and dynamics, as well as the striking differences among the plots.

Let us start with comparing the matrix of pairwise directional connectedness plots with the connectedness table, which is presented in Table 6.3. As expected, the regional pairwise connectedness clusters that are discussed in lieu of the connectedness table are also observed in the dynamic framework of rolling pairwise connectedness plots. The dollar exchange rates of the European currencies, perhaps

[7] The substantial difference between the "to" connectedness plots of the two exchange rates may be due to the lower market turnover in the NZD/USD exchange rate. While the AUD/USD currency pair accounted for 6% of global FX market turnover in 2010, the NZD/USD exchange rate did not even account for 1% of the global FX market turnover (see Table 6.1).

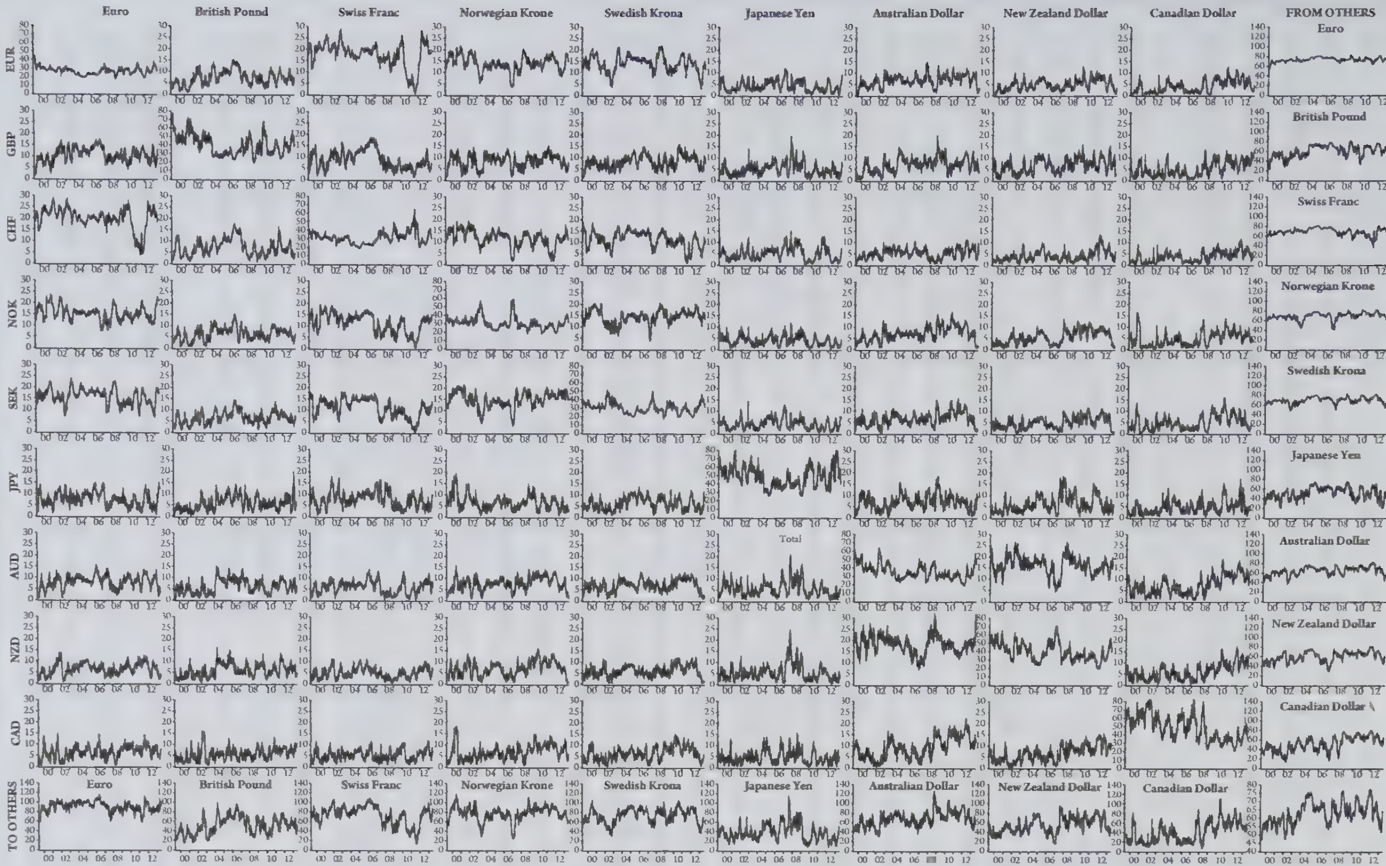


Figure 6.7 Pairwise directional volatility connectedness in FX markets (100-day window).

with the exception of the British pound, tend to have high dynamic pairwise connectedness among each other throughout the period of analysis. Similarly, the pairwise dynamic connectedness measures between the AUD/USD and NZD/USD exchange rates are higher than the other pairs of exchange rates. The pairwise connectedness of USD/CAD with AUD/USD and NZD/USD increased in 2007 and 2008, before declining in 2009 through 2011. The volatility of the two exchange rates started to influence the volatility of the other currencies more and more, as well as being influenced by them in the era of global financial crises.

The EUR/USD is one of the most connected of all exchange rates. It has strong "to" and "from" connectedness with the Swiss franc, the Norwegian krone, and the Swedish krona. To start with, the pairwise connectedness between EUR/USD and USD/CHF was one of the highest in Figure 6.7. The connectedness from EUR/USD to USD/CHF fluctuated between 20% and 25% until the end of 2008. With the recovery gaining momentum in 2009, the connectedness from EUR/USD to USD/CHF increased to almost 30%. The connectedness from USD/CHF to EUR/USD was also high at the beginning, but declined over time, hitting 10% at the end of 2008. During the recovery phase in financial markets, the connectedness from USD/CHF to EUR/USD increased rapidly, reaching 25% in early 2010. However, the pairwise connectedness from EUR/USD to USD/CHF declined sharply, to 5%, in 2010 as the sovereign debt crisis spread from Greece to Portugal and Ireland, and the EU was not able to devise policies that could act as a firewall that would prevent the rest of the EU from plunging into crisis. During this period, the fortunes of the euro and the Swiss franc diverged. As the euro started losing ground against other currencies and became more volatile, the Swiss franc became one of the currencies seen as a safe haven.

The pairwise connectedness of the Swiss franc declined the most vis-à-vis other European currencies. This result is consistent with the safe haven status the Swiss franc has gained in the era of global crises. In response to the constant appreciation of its currency against all major currencies, the Swiss National Bank intervened in the FX markets, leading in part to the decoupling of the Swiss franc from other currencies. The "to" connectedness of the USD/CHF vis-à-vis the EUR/USD declined further, to 1% at the end of 2010, before increasing again at the end of 2011 and in early 2012. The "to" connectedness of the USD/CHF vis-à-vis all other currencies also increased during that period.

Interestingly, its "from" connectedness with the GBP/USD exchange rate spiked close to 20% in the summer of 2011, before coming down quickly by the end of the year. Even though the British pound's "to" connectedness with other currencies also increased during that period, the Swiss franc was the most-affected currency.

The EUR/USD exchange rate has become more connected since the outbreak of the global financial crisis. Its "to" connectedness with the U.S. dollar exchange rates of the Norwegian krone, the Swedish krona, and the Australian, New Zealand, and

Canadian dollars have followed an upward trend since the outbreak of the global financial crisis. Its "from" connectedness with these exchange rates, however, has not increased as much as the "to" connectedness, indicating an increased role of the euro in spreading volatility in FX markets around the world.

The USD/JPY exchange rate is the least connected of all the exchange rates. Its pairwise connectedness to other exchange rates fluctuated between 5% and 10% until the global financial crisis. Starting in 2007, its pairwise "to" and "from" connectedness with GBP/USD, USD/CHF, AUD/USD, and NZD/USD increased and fluctuated between 15% and 20%. Once the U.S. banking system started to emerge from the crisis in the first half of 2009, the pairwise connectedness of the USD/JPY exchange rate to all other exchange rates fell to below 10%.

Finally, in this section we compare the pairwise directional connectedness plots for the major exchange rates with the ones we obtained for the stock and bond markets in previous chapters. There is a substantial difference between the volatility connectedness plots of the exchange rates, on the one hand, and the connectedness plots for the stock and bond markets, on the other. In the case of exchange rates, all major currencies considered belong to industrial countries, and they have been used extensively in both international trade and financial transactions. As a result, the pairwise directional connectedness across the major exchange rates are not negligible.

The same is not true for stock markets. As we have already pointed out above, American, British, German, and French stock markets stand out with significant pairwise directional volatility connectedness among each other and to others, in contrast to little connectedness from others. A similar situation is observed in the case of sovereign bond markets. While the American, British, German, French, Italian, and Greek sovereign bond markets have a rather high pairwise directional connectedness to each other, their connectedness "to" and "from" other bond markets is negligible.

6.A APPENDIX: STANDARD ERRORS AND ROBUSTNESS

Similar to appendices of the previous chapters, in this appendix we start with presenting the full-sample volatility connectedness table (Table 6.A.1), along with the standard errors for total and pairwise connectedness measures obtained through a nonparametric bootstrap method. All pairwise volatility connectedness measures among the major exchange rates vis-à-vis the U.S. dollar are statistically different from zero at the 1% level. All total "net" directional connectedness measures are significant at the 5% level.

Figure 6.A.1 presents robustness of the total exchange rate volatility connectedness plots to variation in forecast horizon, H, and the VAR model order, p. The graphs clearly show that total volatility connectedness plot is quite robust to changes in the forecast horizon h from 6 to 12 days and from 12 to 18 days. The gray-shaded band

Table 6.A.1 Volatility Connectedness Table with Standard Errors, USD Exchange Rates of 9 Major Currencies

	EUR	*GBP*	*CHF*	*NOK*	*SEK*	*JPY*	*AUD*	*NZD*	*CAD*	*FROM*
EUR**	27.6 (0.59)	7.9 (0.46)	16.9 (0.52)	14.7 (0.54)	15.7 (0.45)	2.9 (0.33)	8.0 (0.51)	4.5 (0.41)	1.9 (0.30)	72.4 (0.59)
GBP**	10.2 (0.49)	35.9 (1.43)	7.9 (0.49)	10.6 (0.58)	9.9 (0.57)	3.4 (0.48)	9.0 (0.66)	7.3 (0.62)	5.8 (0.67)	64.1 (1.43)
CHF**	20.7 (0.44)	7.5 (0.45)	31.3 (0.81)	12.2 (0.51)	12.0 (0.41)	3.7 (0.37)	6.2 (0.47)	3.9 (0.38)	2.4 (0.34)	68.7 (0.81)
NOK**	14.9 (0.45)	7.8 (0.55)	10.1 (0.47)	28.8 (0.86)	15.9 (0.49)	2.7 (0.35)	8.8 (0.56)	6.0 (0.50)	5.1 (0.58)	71.2 (0.86)
SEK**	15.8 (0.44)	7.6 (0.53)	9.9 (0.46)	16.1 (0.51)	29.1 (0.81)	2.9 (0.39)	9.1 (0.59)	5.6 (0.52)	3.8 (0.49)	70.9 (0.81)
JPY**	6.4 (0.56)	5.2 (0.63)	6.3 (0.59)	6.2 (0.59)	5.9 (0.60)	53.6 (2.26)	8.1 (0.70)	5.9 (0.65)	2.3 (0.44)	46.4 (2.26)
AUD**	8.0 (0.52)	6.4 (0.59)	5.0 (0.47)	9.3 (0.58)	8.7 (0.59)	5.0 (0.56)	34.2 (1.20)	17.2 (0.74)	6.0 (0.63)	65.8 (1.20)
NZD**	6.2 (0.50)	6.6 (0.59)	4.1 (0.44)	8.4 (0.57)	7.6 (0.59)	4.5 (0.56)	21.8 (0.74)	36.1 (1.35)	4.7 (0.58)	63.9 (1.35)
CAD**	2.9 (0.45)	7.8 (0.94)	2.9 (0.48)	8.9 (0.97)	5.4 (0.69)	2.0 (0.48)	9.4 (0.85)	6.6 (0.82)	54.1 (2.69)	45.9 (2.69)
TO**	85.1 (2.38)	56.9 (3.47)	63.1 (2.67)	86.4 (3.13)	81.1 (3.05)	27.0 (2.79)	80.5 (3.51)	57.0 (3.34)	32.1 (3.26)	
NET	12.7** (2.41)	−7.2* (3.54)	−5.5* (2.48)	15.2** (3.16)	10.2** (3.18)	−19.5** (2.78)	14.7** (3.74)	−6.8* (3.49)	−13.8** (3.78)	**63.2**** (0.96)

Notes: See the footnote in Table 6.3.

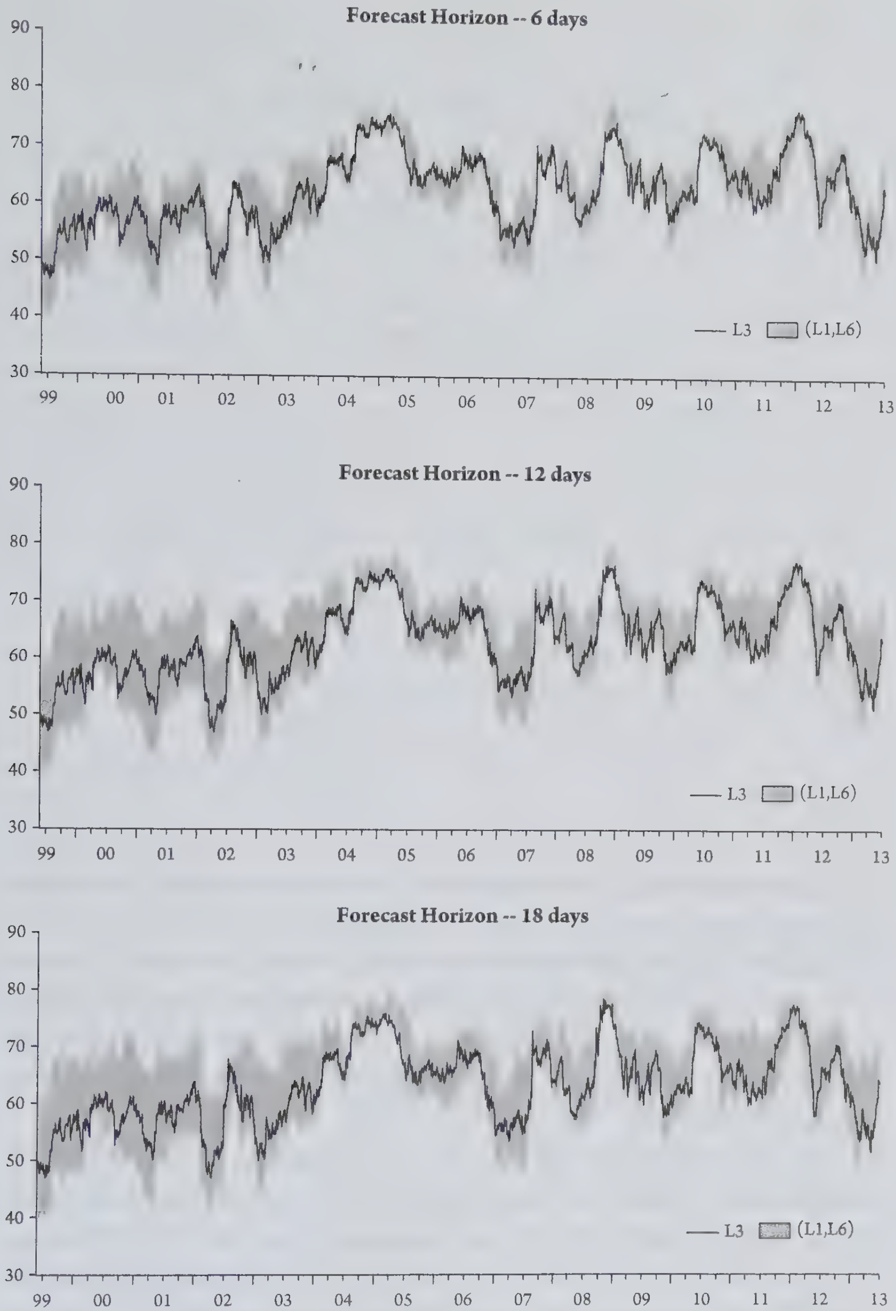


Figure 6.A.1 Robustness to forecast horizon and lag choice, total FX market volatility connectedness. See the footnote of Figure 2.A.1.

that shows the sensitivity of the total connectedness to the VAR model order p becomes wider as we increase the forecast horizon. However, despite the sensitivity to VAR lag length, our benchmark model of $H = 12$ and $p = 3$ still represents the temporal variation in the total volatility connectedness across exchange rates quite well.

7

ASSETS ACROSS COUNTRIES

After focusing on the connectedness among four asset classes in the United States in Chapter 2, we separately analyzed connectedness for each of stocks, bonds, and foreign currency asset classes across countries in Chapters 4 through 6. The separate analyses of each of these asset classes help us uncover more about the dynamics of connectedness of each asset market across countries at various junctures over the last decade and a half. For completeness, it is crucial to undertake the connectedness analysis across asset classes and countries.

Analyzing connectedness of just one asset class across many countries leaves aside the connectedness across asset classes within the same country. When there is a return or volatility shock to an asset class in a country, the effect of this shock can potentially spill over to other assets in the same country. For example, when the FX market volatility increases all of a sudden due to an announcement by the government and/or the central bank, the increased FX market volatility may cause the stock market volatility increase as well. On the other hand, studying connectedness across asset classes within a single country leaves aside the connectedness of the volatility of a single asset across countries and how it affects the connectedness of different assets within the same country. Without taking the interaction between connectedness across assets and countries into account, we will be missing possibly an important source of connectedness that will have serious implications for all types of assets.

7.1 FOUR ASSET CLASSES IN FOUR COUNTRIES

The empirical analysis of connectedness across assets and countries covers 13 and a half years, from January 1999 to June 2013. Due to limitations on the number of variables included in the connectedness analysis, we include only four countries/regions (United States, European Union, United Kingdom, and Japan) in the analysis. This implies that we will have 12 variables in the VAR analysis. For every country, three asset classes are included: stocks, long-term sovereign bonds, and foreign exchange (exchange rate of their respective currencies vis-à-vis the U.S. dollar). As a result, there are only two assets for the United States, namely, stocks and government bonds. In addition, we include the Dow Jones–UBS Commodity index to account for the volatility in commodity markets as a whole.

We would have liked to include China, the rapidly rising global economic power, in the analysis, but we are not able to do so for several reasons. First, we cannot include Yuan-Dollar exchange rate in the analysis because Yuan does not have a freely floating exchange rate vis-à-vis the U.S. dollar. Furthermore, Chinese bond market data are not available all the way back to the early 2000s. The only Chinese asset market that we can include in the analysis is the stock market. However, as we have seen in Chapter 4, the Chinese stock market did not appear to have a high degree of connectedness with the other nine stock markets included in the analysis. Therefore, we think that an analysis of four asset classes across four countries/regions is not very restrictive and will help us to uncover a significant degree of connectedness that have taken place across financial asset classes around the world.

7.2 FULL-SAMPLE VOLATILITY CONNECTEDNESS

The static volatility connectedness table is presented in Table 7.1. The static total volatility connectedness, 42.2%, is higher than the really low full-sample total connectedness for the U.S. asset classes in Chapter 2, 15.9%, and very close to the full-sample total connectedness across global stock markets, 41%.

A closer look at the connectedness table reveals several results we would like to analyze briefly. First of all, the "to" and "from" connectedness measures vary substantially across asset classes and countries. Japan turns out to have the lowest "to" and "from" connectedness, especially in stock and bond markets. Actually, the Japanese bond market has the lowest "to" and "from" connectedness (5.4% and 11.8%, respectively). However, despite having the lowest "to" and "from" connectedness, the

Table 7.1 Volatility Connectedness Table with Standard Errors, Four Assets Across Four Countries

		Stocks				*10-Year Government Bonds*				*FX with Respect to USD*				
		US	*EU*	*UK*	*JPN*	*US*	*GER*	*UK*	*JPN*	*EUR*	*GBP*	*JPY*	*Commodity*	*FROM*
Stocks	US	47.7	15.6	18.6	2.7	5.0	2.3	1.3	0.1	2.7	1.7	1.9	0.4	52.3
	EU	17.0	40.6	23.5	2.1	3.3	4.6	2.2	0.7	3.1	1.4	1.2	0.3	59.4
	UK	19.0	22.4	41.5	2.3	3.0	3.6	2.2	0.2	2.0	1.5	1.8	0.5	58.5
	JPN	9.0	6.0	7.5	65.3	1.4	0.4	0.2	2.1	1.3	0.9	5.6	0.2	34.7
Bonds	US	9.2	6.3	6.7	0.7	51.8	9.0	5.3	0.3	4.1	2.8	3.1	0.6	48.2
	GER	4.0	7.4	6.6	0.1	7.8	49.2	15.2	0.4	4.4	2.0	1.5	1.3	50.8
	UK	3.6	4.6	6.0	0.03	5.8	18.0	52.2	0.3	3.2	2.9	2.2	1.2	47.8
	JPN	0.8	0.5	0.3	4.0	1.8	0.5	0.6	88.2	0.2	0.2	2.8	0.1	11.8
FX	EUR	5.7	4.9	4.5	0.5	3.6	4.6	2.4	0.1	51.8	16.4	5.2	0.5	48.2
	GBP	3.9	2.3	3.4	0.5	2.4	1.8	1.8	0.1	17.0	56.2	5.1	5.7	43.8
	JPY	4.5	2.4	3.6	2.9	3.8	2.1	2.6	1.0	7.2	6.1	63.0	0.9	37.0
Commodity		0.9	0.5	1.2	0.6	0.5	1.4	1.0	0.1	0.4	5.8	0.8	86.7	13.3
TO		77.6	72.8	81.8	16.3	38.4	35.0	48.3	5.4	45.7	41.6	31.3	11.7	
NET		25.3	13.4	23.3	−18.3	−9.7	−12.8	−2.4	−6.4	−2.5	−2.3	−5.8	−1.6	**42.15**

Notes: The sample is taken from January 3, 1999 through June 28, 2013. All but the underlined connectedness measures are statistically different from zero at the 1% or 5% level. Bootstrapped standard errors are presented in this chapter's appendix, in Table 7.A.1.

Japanese bond market has negative net connectedness, indicating that its a net recipient of volatility shocks from other countries and/or asset classes. The commodity markets have the second lowest "to" and "from" connectedness (11.7% and 13.3%) measures, respectively. As its "to" and "from" connectedness measures are not too wide apart, its "net" connectedness is not statistically different from zero.

The net total connectedness row at the bottom of the table shows that stock markets in the United States (25.3%), the United Kingdom (23.3%), and the European Union (13.4%) are net transmitters of volatility shocks. Other markets included in the analysis are the recipients: They all have negative net connectedness, but only the net connectedness measures for the Japanese stock market (–18.3%) and for the bond markets in Germany (–12.8%), the United States (–9.7%), and Japan (–6.4%) are statistically different from zero. We think that this is an important result in that it reveals the hierarchy among the asset classes in terms their reflections of the overall economy. Forward-looking stock markets act like the barometer for the whole economy. When the investors in stock markets become increasingly worried and panicked about the future state of the economy, this leads to sharp increases in stock index return volatility. The results show that other asset markets cannot escape unscathed from the rapid increase in volatility in stock markets. Obviously as we saw in earlier chapters, the recent global financial crisis is a good example where the volatility connectedness among the global stock markets as well as in other asset classes increased substantially.

Third, more than half of the directional connectedness takes place within the same asset class across countries. The total connectedness within the same asset class across countries is 22.3%, whereas the total connectedness across assets (in the same country or across countries) is 19.8%. This result is consistent with our findings in Chapter 2: The total connectedness across four assets within the U.S. economy was very low at 15.9%. As we focus further, we observe that the bulk of the within asset class connectedness (12.2%) takes place among the four stock markets; the contributions of the within bond market and the within FX market connectedness are much less (5.4% and 4.7%, respectively) compared to the one observed across stock markets.

Fourth, Japanese detachment from the global markets is quite visible in Table 7.1. Even though the other three stock markets in our analysis have significant volatility effects on other markets, the Japanese stock market has large negative net connectedness. This is consistent with what we observed in Chapters 4 and 5. Since the 1990s, Japanese stock and bond markets have lost their importance for the global financial markets. The Japanese yen differs from the Japanese bond and stock markets in terms of connectedness. Its "to" and "from" connectedness measure is higher than 30%, unlike the Japanese bond and stock markets, even though its net connectedness is not statistically different from zero. Even though the Japanese yen is still one of the more important currencies for the world economy, the Japanese stock and bond markets are not as important for the global financial system.

Focusing on pairwise directional volatility connectedness, the U.S. stock market is the only market that has positive net pairwise connectedness with all others. Its net connectedness with the Japanese stock market is 6.3%, and the net connectedness with the U.S., the German, and the UK bond markets are 4.2%, 2.3%, and 1.7%, respectively. The net connectedness of the UK and the EU stock markets with the Japanese stock market are also relatively high: 5.2% and 3.9%, respectively. The net connectedness of the U.S., UK, and the EU stock, bond, and FX markets within the same asset class are in general less than 1.5%, indicating that the corresponding markets are equally connected with other markets in the same asset class.

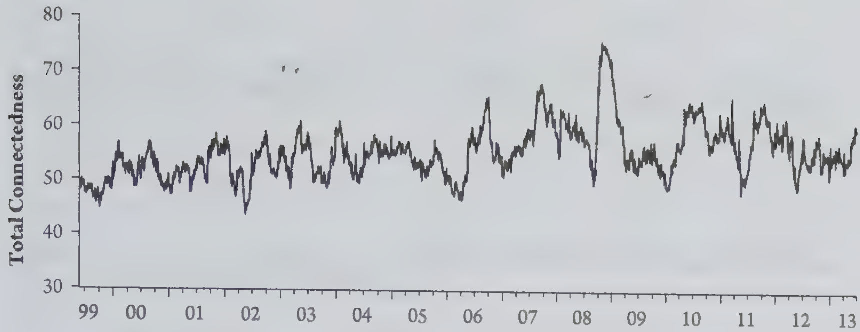
7.3 DYNAMICS OF VOLATILITY CONNECTEDNESS

7.3.1 Total Connectedness

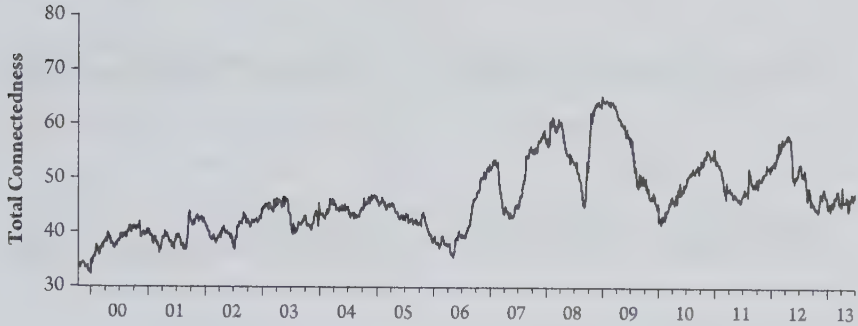
In the analysis of the four-country case, we use 100-day rolling sample windows. However, the results are robust to the sample-window choice. There is little change in the total connectedness plot when we use 200-day rolling sample windows. Both 100-day and 200-day window plots are presented in Figures 7.1(a) and 7.1(b). The 200-day window analysis allows us to interpret the results better in a dynamic framework, as it provides a smoother connectedness plot. The 100-day window is also important because it helps us identify and analyze the impact of "less important" shocks on the volatility connectedness across asset markets and countries.

The period from 1999 through the first half of 2006 was mostly uneventful compared to the period from mid-2006 to late 2009. Furthermore, the short-lived upward movements in the volatility connectedness in the years from 2000 through 2004 were relatively small compared to the fluctuations in the period from mid-2006 to 2012. Focusing on the connectedness plot with a 200-day window, one can easily observe that the index fluctuated between 32% and 47% over the period from 1999 to mid-2006. We observe a similar behavior of the index when we use the 100-day rolling window to measure it. In the 100-day window plot, the total connectedness index fluctuated between 44% and 61% over the period from 1999 to mid-2006

The first increase in total volatility connectedness (from 45% to 57% in 2000) was a result of the burst of the U.S. tech-stock bubble in early 2000. Following this episode, the index fell below 50% in early 2001, to increase once again following the September 11 terrorist attacks in the United States (see Figure 7.1(a)). During the tech-bubble burst that started in 2000 but lasted until mid-2001, the net volatility connectedness of the U.S. stock market increased to above 40% and fluctuated around that level



(a) 100-day window



(b) 200-day window

Figure 7.1 Total volatility connectedness across asset classes and countries (January 1999–June 2013).

until mid-2001. During this period, net connectedness of the European and UK stock markets were also positive (fluctuating between 10 and 20%), but the Japanese stock market's net connectedness was generally negative in this period (Figure 7.2). The Dow Jones–UBS commodity index generated substantial net connectedness in 2001, both before and after the September 11 attacks. Finally, net volatility connectedness of the euro-dollar exchange rate was positive during this period, reaching as high as 30% in the summer of 2001.

After falling down in early 2002, the index increased approximately 13 points following the bankruptcy of the U.S. telecommunications giant MCI WorldCom on July 19, 2002. As we have discussed in Chapters 2 and 4, following the MCI WorldCom debacle on July 2002, the net connectedness of the U.S. stock market jumped up to 40% within a month (Figure 7.2).

The net volatility connectedness of the EU and the UK stock markets went up even before the increase in the connectedness of the U.S. stock market. The connectedness of the EU stock market increased to close to 45% in early summer of 2002 and stayed high until the last quarter of 2002. The net connectedness of the UK stock market also increased throughout 2002 to around 20% by the end of the year. Both the EU and the UK stock markets suffered significantly, and more than the U.S. market

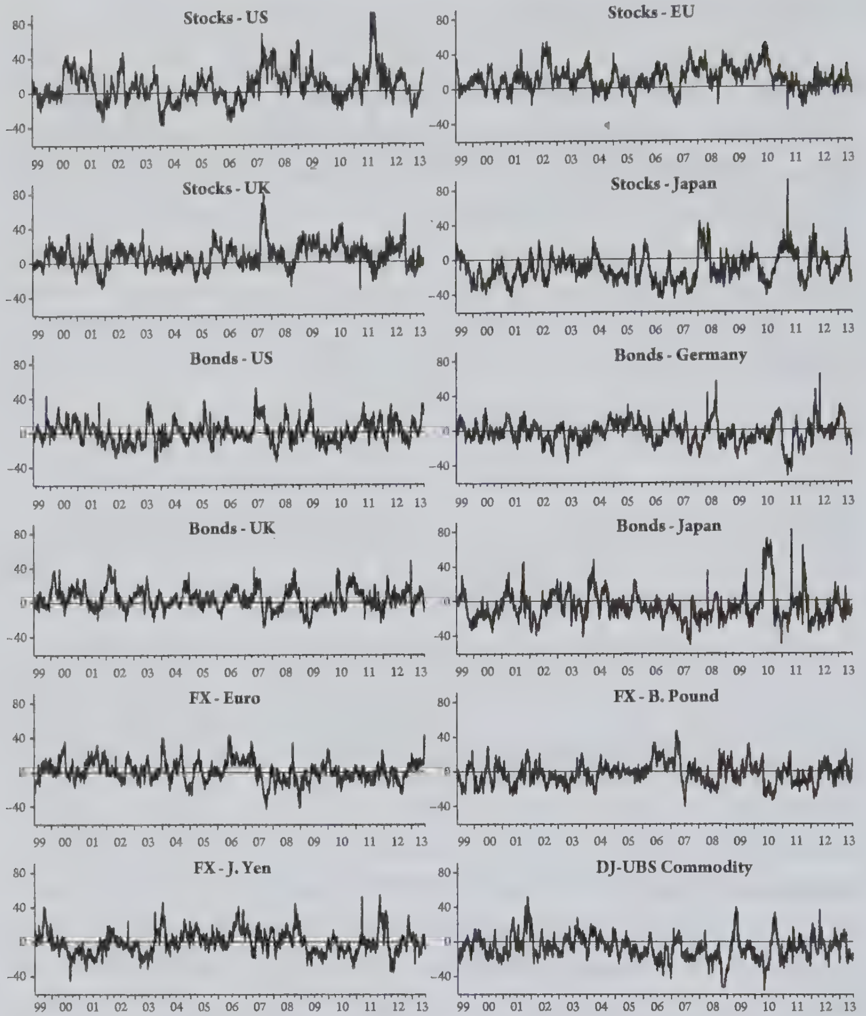


Figure 7.2 Net directional volatility connectedness across asset classes and countries (100-day window).

throughout 2002. From the beginning of March 2002 to the end of September 2002, both the S&P 500, the Euro Stoxx 50, and the FTSE 100 indices gave up approximately 25% of their respective values. The decline in the value of the European stocks was much sharper compared to that of the U.S. stocks. Among other markets in the analysis, only the German government bond market returns and the DJ–UBS commodity index recorded some increase in their respective net volatility connectedness measures. All other markets were on the receiving end of the spectrum.

The index increased once again in early 2003 as the U.S. government intensified its efforts to form a coalition of countries to go to war against Iraq. As the invasion of Iraq by U.S.-led forces started in mid-March 2003, the index increased 12 percentage points to reach 61% by the end of the war in mid-May 2003 (see Figure 7.1(a)). As a result of the Iraqi war tensions, the net connectedness of the U.S., the UK, and the EU stocks increased again to reach around 20% (Figure 7.2).

The total connectedness index increased in November–December 2003 again (approximately 12-point increase in the 100-day window). This time around the source of the increased connectedness was the FX market. The euro–dollar parity increased by 30%, from mid-April 2002 to the end of September 2003. In response to the upward trend in the euro–dollar parity, officials from oil-exporting countries and OPEC publicly contemplated on trading in euro or in a basket of currencies instead of the dollar. As a result of these remarks, in December 2003 the speculation about the future roles of the dollar and the euro in international markets intensified. The dollar depreciated against the euro and the pound further; the volatility of the euro and pound exchange rates vis-à-vis the dollar increased. Despite speculations, no decision to move to oil trading in the euro was taken at the OPEC meeting on February 10, 2004 (see Nunan (2004)). Following the meeting, the euro–dollar exchange rate started to depreciate while the volatility in FX markets subsided. From mid-2003 to mid-2006, the net volatility connectedness of the U.S. stocks was mostly in the negative territory, but the net volatility connectedness of the EU stock markets increased in the second half of 2003 to reach close to 40% by the first quarter of 2004. At the end of 2003, the net connectedness of the euro and the Japanese yen exchange rates vis-à-vis the U.S. dollar and the Japanese bond market increased significantly to reach the 40% level each.

Following the 12-point increase at the end of 2003, the volatility connectedness declined back to around 50% by May 2004. From mid-June onward, however, the index recorded an 8-percentage-point increase to reach 58% by September 2004 (Figure 7.1(a)). The increase in total connectedness in mid-June through September 2004 followed the Fed's decision to tighten the monetary policy. FX and bond markets generated positive net connectedness during this episode. The net connectedness of the euro–dollar exchange rate increased the most, reaching above 30% by September 2004 (Figure 7.2). The total connectedness index did not decrease much after September 2004. It fluctuated between 50% and 60% until May 2005. The 7-percentage-point increase in the total volatility connectedness in August through October 2005 was mostly due to the increase in the net connectedness of the UK and U.S. stocks.

As we have highlighted in previous chapters, from May 2006 onward, total volatility connectedness increased in almost all financial markets. Consistent with those results, we observe a similar drastic change in the behavior of total volatility connectedness across asset classes and countries after May 2006. Following the Fed's decision to further increase its policy rate led to unwinding of dollar carry trades in emerging markets and the European countries. As a result, the total connectedness index increased from a low of 47% in early April to 66% in mid-September 2006. All three exchange rates started to generate positive net connectedness after the Fed's decision. In June 2006, the net volatility connectedness of the euro–dollar and pound–dollar exchange rates went up to reach 40% and 30%, respectively. The increase in net connectedness of the dollar–yen exchange rate was limited at first, but went up to reach 40% in mid-September. Net connectedness of the EU and British stocks also increased during this episode to reach 30%. Net connectedness of the U.S. and Japanese stock markets were positive but quite low. Among the bond markets, net connectedness of the U.S. government bond market jumped to 18% by late May 2006 but then subsided, whereas net connectedness of the German and British bond markets moved gradually from –20% in June 2006 toward 20% in late 2006.

As the observations for mid-2006 are left out of the 200-day rolling window, the index declined. It was around 52% as of the beginning of 2007. However, with the first signs of the U.S. mortgage crisis the index started to move up. In late January and in late February 2007, there were two brief but sharp downturns in the Shangai Stock Exchange composite index. These two, combined with the collapse of several sub-prime mortgage originators in late February, led to a gradual increase in the connectedness index from 52% to reach 58% by June. The collapse of Bear Stearns' two hedge funds occurred in June, followed by the liquidity crisis of August 2007. The liquidity crisis showed that the mortgage crisis would have direct implications for the major European as well as the American banks. As a consequence, the index jumped up by 10 points and reached 68%.

During the liquidity crisis, most of the volatility connectedness was generated by the U.S. and European stock markets and the U.S. bond market. While the net connectedness of the American and British stocks fluctuated between 40% and 60%, that of the EU stocks fluctuated between 30% and 40%. As the international markets started to calm down following the liquidity crisis, bad news from the United Kingdom rocked the markets again. On September 13, it was announced that the British bank Northern Rock applied for and granted emergency financial support from the Bank of England as the lender of last resort. Immediately following the news, the UK stock market's net volatility connectedness jumped to 78% on September 18. The Japanese stock market, on the other hand, mostly had negative connectedness through the early phase of the financial crisis.

Even though the American banks started to announce huge losses one after the other and the net connectedness of the American banks stayed high, in the following several months the total connectedness index gradually declined to fall below 55% by the beginning of 2008. On January 22, 2008, in an inter-meeting conference call the FOMC voted to lower the Fed funds' target rate by 75 basis points. In its January

30 meeting, the FOMC reduced the Fed funds' target rate by another 50 basis points. The markets interpreted the FOMC's decision as a revelation of how bad the situation could get. On January 23, the volatility connectedness across asset classes and countries jumped by another 3 percentage points. The U.S. stock market continued to have high (fluctuating around 50%) net connectedness throughout the last quarter of 2007 and the first quarter of 2008.

Market gyrations continued throughout 2008. In March, Bear Stearns was taken over by J.P. Morgan through a deal orchestrated by the government. Even though the losses in the major continued to climb, there were no major jump in the index until September. In the first two weeks the index increased slightly following the news of government takeover of Fannie Mae and Freddie Mac. The announcement of the bankruptcy of Lehman Brothers on September 15 led to the largest jump in the history of the index. From 52% value on September 12, the index jumped from 55% on September 15, to 62.5% on September 22, and to 67% by the end of the month. It continued its upward move throughout October, hitting its maximum value (76.3%) on October 28.

The collapse of Lehman Brothers and the ensuing developments were critical because that was when the U.S. financial crisis was transformed into a global financial crisis. When we have a closer look at Figure 7.2, we observe that during this rather fluid episode the net volatility connectedness of the U.S. stock market and the German bond market (representing the European bond market) increased all the way up to 40%, indicating that these markets contributed to the total volatility connectedness index the most. However, their high net connectedness declined all the way down to zero during early 2009.

Total volatility connectedness declined constantly after hitting the maximum at the end of October 2008. By the end of 2009, the index was back to the levels (low forties) it was fluctuating around before the Lehman's collapse. However, it did not decrease any further. The debt crisis in the EU periphery had become a haunting reality with the announcement of Greece's fiscal problems at the end of 2009. As we already have discussed above, the Greek sovereign debt crisis was not addressed quickly by the EU and turned into a serious debt and banking crisis affecting the financial markets around the world. As a result, in December 2009 the total connectedness index started to increase again from the 42% level to reach 66% by June 2010. Toward the end of 2010, Irish debt problems resurfaced as the Irish government had to renew its guarantees for six banks (for more see Chapter 4). The index rose for several percentage points to reach the low 60s.

The index increased again in the summer of 2011 as the Italian and Spanish sovereign debt worries intensified; then in May–June 2012 as another round of Greek debt problems surfaced along with the fast approaching uncertain Greek elections and, finally, following the Fed's announcements about the gradual tapering of the quantitative easing policies.

In the cross-country cross-asset framework, what goes up fast comes down fast as well. As the observations pertaining to the crisis episodes are left out of the rolling sample window, the total connectedness index goes down to its pre-crisis level. In that regard, the connectedness across assets and countries will differ from the connectedness across countries within the same asset class. In the case of stock markets in Chapter 4, the volatility connectedness index increased over time after the outbreak of the global financial crisis in 2008 (see Figure 4.3(b)).

7.3.2 Pairwise Directional Connectedness

Above we discussed the behavior of the total directional connectedness of each market over time along with the total connectedness index. In this section, we rather focus on the pairwise directional connectedness to analyze the links between asset classes across countries over time.

When we focus on the pairwise connectedness graphs in Figure 7.3, we obtain the most important result of the analysis of volatility connectedness across asset classes and countries: The bulk of volatility connectedness takes place within the same asset class and across countries rather than across different asset classes within the same country. The rather high levels of pairwise connectedness in the 4×4 matrix (or, rather, the 3×3 matrix) of graphs in the upper-left corner of Figure 7.3 show that pairwise connectedness across stock markets in four (or, rather, three excluding Japan) countries is much higher than connectedness from stock markets to other asset classes. Similarly, the rather high connectedness measures in 3×3 graphs located around the center of Figure 7.3, show that the pairwise connectedness of the U.S., the EU, and the UK bond markets tend to be higher among each other. As we have highlighted above, the pairwise connectedness of Japanese government bond market with the other three bond market is rather low. Similarly, the pairwise connectedness of the FX markets tend to be much higher among each other, then with other asset classes in the same or other countries. Unlike the case with the stock and bond markets, Japan is not left out of the loop in the connectedness of foreign exchange rates vis-à-vis U.S. dollar. Dollar–yen exchange rate also has sizable pairwise connectedness measures with the other two currencies. Finally, the pairwise volatility connectedness of the commodity markets is rather low with all asset classes in all four countries.

We think that the result we summarized in the previous paragraph is very important: Volatility connectedness is much stronger within the same asset class irrespective of the country in which the market is located. This finding is consistent with the results we reported in earlier chapters. It implies that volatility in stock, bond,

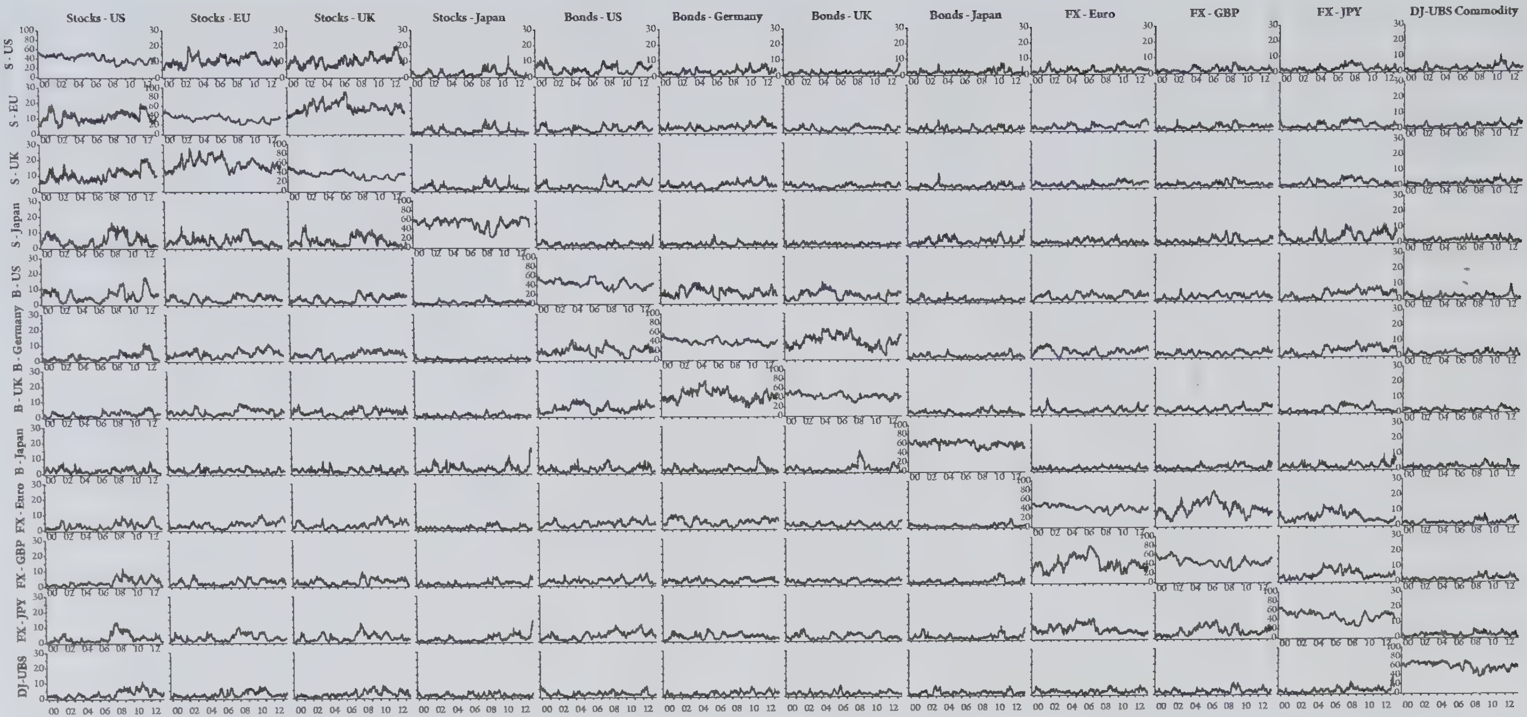


Figure 7.3 Dynamic directional volatility connectedness across asset classes and countries (200-day window).

FX, and commodity markets are not necessarily driven by the same underlying factors even if they are located in the same country. Positive volatility shocks in stock markets may not necessarily lead to higher volatility in bond, FX, and/or commodities markets.

This finding implies that when there is a return volatility shock to an asset class in one of the countries, the shock generates connectedness across the same asset class in different countries, rather than across different asset classes within the same country. As we reported in Chapter 2, during the climax of the U.S. financial crisis the total volatility connectedness across four U.S. asset classes reached only 30%. Whereas over the same time period the volatility connectedness across 10 global stock markets or across 10 global bond markets went as high as 65%, the volatility connectedness across major exchange rates went up as high as 80% (see Chapter 4). Obviously, with only four markets the volatility connectedness across the U.S. asset classes can be expected to be lower than the connectedness analyses among 10 stock or bond markets. Yet, jumps in volatility connectedness measures during crises tend to be much larger across the countries within the same asset class compared (Chapters 4 and 5) to the ones we observed across the asset classes within the same country (Chapter 2).

Another result of the analysis concerns the timing of significant jumps in the total connectedness index. Actually, this is a common finding of all empirical chapters of the book: The return or volatility connectedness can arise not only during the major financial crises but also following important policy decisions that force investors to revise their investment strategies (Fed's decision to start raising the Fed funds target rate in 2004 and Fed's decision to continue raising the Fed funds target rate in May–June 2006). In addition, volatility connectedness can be high following some political events or terrorist attacks that might suddenly increase volatility in asset markets (9/11 terrorist attacks, for example).

While the bulk of the connectedness took place within the same asset class across countries, it does not mean that there was no volatility connectedness across asset classes irrespective of the location of the market. As can be seen in Figure 7.4 for the case of 200-day windows, in the early 2000s and since 2007 the direction of net volatility connectedness has been from the stock markets to bond markets, on the one hand, and FX and commodity markets on the other.[1] There was no substantial net volatility connectedness from bond markets to stock markets at any time. While the net volatility connectedness from stocks to bonds had occasionally moved to negative territory (which means the net connectedness from bonds to stocks is positive) from late 2003 through the first quarter of 2006, it never reached above the 20% level in absolute

[1] We treated commodity market index together with the three FX rates even though we know that they are governed by distinct processes.

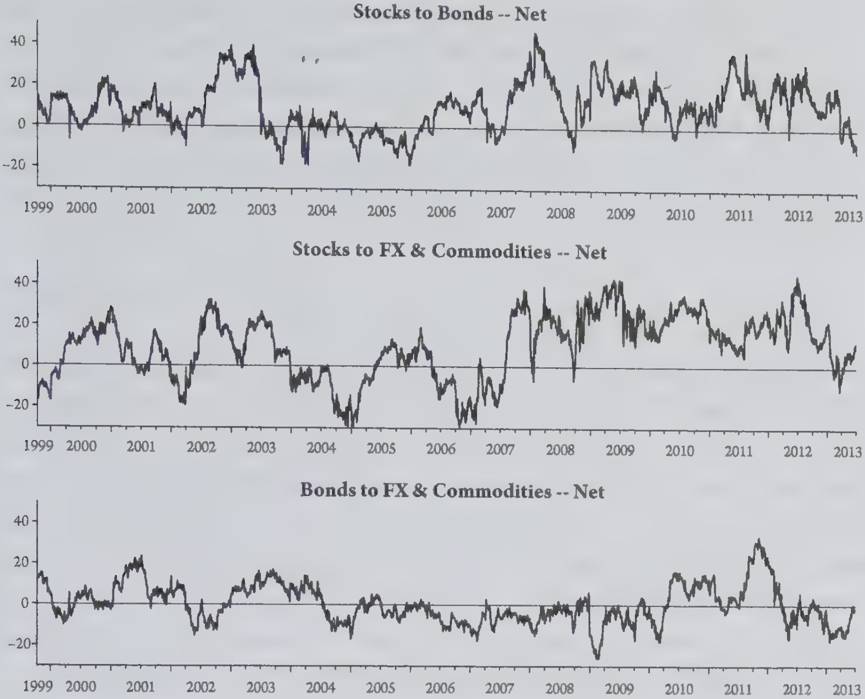


Figure 7.4 Net volatility connectedness across asset classes (January 1999–June 2013).

value. In the case of FX markets, net volatility connectedness to stocks reached to 30% in late 2004 and early 2005, and in late 2006 early 2007, following the Fed's May–June 2006 decision to tighten monetary policy one notch further.

Bond markets' net connectedness to FX and commodity markets increased to around 20% in 2001 and 2003, and to between 20% and 30% in 2010 and 2011, during the European banking and sovereign debt crisis. Other than these periods, the direction of the net volatility connectedness was from FX and commodity markets to bond markets for most of the period. After reaching 15% and 20% in 2002 and 2004, the net connectedness from FX and commodity to bond markets fluctuated around 10% in the second half of 2006 and in 2007. It increased again in late 2008–early 2009 to reach 25%, its maximum level. After the global financial crisis, the net connectedness from FX and commodities fluctuated below 20% in the second half of 2009, in the first quarter of 2010, and in the second half of 2012 through May 2013.

Let us make another observation from Figure 7.4: The first time the net volatility connectedness across three asset classes fluctuated closer to the zero line since 2007 was in the first half of 2013. One can interpret this fact as the financial markets finally moving out of the long shadow of the global financial crisis and its close cousin European debt and banking crisis. When we look at the total volatility connectedness plots in Figure 7.1, in the first half of 2013 the 100-day and 200-day rolling-window-based total volatility connectedness indices tend to be close to their corresponding values in the pre-crisis period. Even though the 100-day window-based plot seems to be affected by the talk about the U.S. Fed's imminent tapering of its quantitative easing program, the current values of the corresponding total connectedness indices tend to support the conclusion we obtain from the net connectedness measures.

7.A APPENDIX: STANDARD ERRORS AND ROBUSTNESS

We start this appendix with the full-sample volatility connectedness table in Table 7.A.1 along with the standard errors for total and pairwise connectedness measures obtained through nonparametric bootstrap method. All pairwise connectedness measures exceeding 0.8% in size are statistically different from zero at the 5% level or below. Majority of the "to" and "from" connectedness measures of the Japanese bond market, and the "to" connectedness measures of the Japanese stock market are not statistically different from zero.

Figure 7.A.1 presents robustness of the total volatility connectedness across assets and countries plots to variation in forecast horizon, H, and the VAR model order, p. The sub-graphs in Figure 7.A.1 clearly show that a total volatility connectedness plot is robust to changes in the forecast horizon H from 6 to 12 and then to 18 days. However, as can be deduced from the widening in the gray-shaded band, the connectedness plot is more sensitive to changes in the lag choice especially in pre-2007, for $H = 12$ or $H = 18$. However, our benchmark model with $H = 12$ and $p = 3$ captures the time variation in total connectedness quite well since 2007.

Table 7.A.1 Volatility Connectedness Table with Standard Errors, Assets Across Countries

		Stocks				*10-Year Government Bonds*				*FX with Respect to USD*				
		US	*EU*	*UK*	*JPN*	*US*	*GER*	*UK*	*JPN*	*EUR*	*GBP*	*JPY*	*COM*	*FROM*
S	US	47.7**	15.6**	18.6**	2.7**	5.0**	2.3**	1.3**	0.1	2.7**	1.7**	1.9**	0.4**	52.3**
t		(1.74)	(0.93)	(1.02)	(0.68)	(0.67)	(0.54)	(0.4)	(0.13)	(0.59)	(0.49)	(0.52)	(0.14)	(1.74)
o	EU	17.0**	40.6**	23.5**	2.1**	3.3**	4.6**	2.2**	0.7*	3.1**	1.4**	1.2**	0.3*	59.4**
c		(1.02)	(1.23)	(0.92)	(0.56)	(0.57)	(0.63)	(0.4)	(0.35)	(0.53)	(0.39)	(0.33)	(0.11)	(1.23)
k	UK	19.0**	22.4**	41.5**	2.3**	3.0**	3.6**	2.2**	0.2	2.0**	1.5**	1.8**	0.5*	58.5**
s		(1.08)	(0.90)	(1.33)	(0.61)	(0.58)	(0.59)	(0.5)	(0.17)	(0.44)	(0.44)	(0.47)	(0.21)	(1.33)
	JPN	9.0**	6.0**	7.5**	65.3**	1.4**	0.4	0.2	2.1**	1.3*	0.9*	5.6**	0.2	34.7**
		(1.16)	(0.94)	(1.04)	(2.78)	(0.53)	(0.27)	(0.2)	(0.59)	(0.55)	(0.43)	(0.98)	(0.23)	(2.78)
B	US	9.2**	6.3**	6.7**	0.7*	51.8**	9.0**	5.3**	0.3	4.1**	2.8**	3.1**	0.6**	48.2**
o		(0.79)	(0.66)	(0.69)	(0.28)	(2.03)	(0.80)	(0.6)	(0.15)	(0.53)	(0.46)	(0.45)	(0.24)	(2.03)
n	GER	4.0**	7.4**	6.6**	0.1	7.8**	49.2**	15.2**	0.4*	4.4**	2.0**	1.5**	1.3**	50.8**
d		(0.60)	(0.66)	(0.67)	(0.09)	(0.80)	(1.66)	(1.0)	(0.22)	(0.52)	(0.42)	(0.29)	(0.39)	(1.66)
s	UK	3.6**	4.6**	6.0**	0.03	5.8**	18.0**	52.2**	0.3	3.2**	2.9**	2.2**	1.2**	47.8**
		(0.57)	(0.56)	(0.69)	(0.07)	(0.65)	(0.99)	(2.0)	(0.18)	(0.50)	(0.50)	(0.42)	(0.39)	(1.96)
	JPN	0.8	0.5*	0.3	4.0**	1.8**	0.5	0.6*	88.2**	0.2	0.2	2.8**	0.1	11.8**
		(0.40)	(0.25)	(0.26)	(0.92)	(0.61)	(0.29)	(0.3)	(1.79)	(0.23)	(0.26)	(0.79)	(0.20)	(1.79)

continued

Table 7.A.1 (continued)

		Stocks				*10-Year Government Bonds*				*FX with Respect to USD*				
		US	*EU*	*UK*	*JPN*	*US*	*GER*	*UK*	*JPN*	*EUR*	*GBP*	*JPY*	*COM*	*FROM*
F	EUR	5.7**	4.9**	4.5**	0.5	3.6**	4.6**	2.4**	0.1	51.8**	16.4**	5.2**	0.5*	48.2**
X		(0.73)	(0.58)	(0.60)	(0.25)	(0.50)	(0.54)	(0.4)	(0.10)	(1.53)	(0.89)	(0.57)	(0.24)	(1.53)
	GBP	3.9**	2.3**	3.4**	0.5	2.4**	1.8**	1.8**	0.1	17.0**	56.2**	5.1**	5.7**	43.8**
		(0.70)	(0.50)	(0.65)	(0.28)	(0.46)	(0.42)	(0.4)	(0.10)	(0.94)	(1.88)	(0.70)	(0.94)	(1.88)
	YEN	4.5**	2.4**	3.6**	2.9**	3.8**	2.1**	2.6**	1.0**	7.2**	6.1**	63.0**	0.9**	37.0**
		(0.73)	(0.45)	(0.63)	(0.64)	(0.53)	(0.42)	(0.5)	(0.35)	(0.72)	(0.75)	(2.09)	(0.35)	(2.09)
Commodity	0.9**	0.5*	1.2*	0.6	0.5	1.4*	1.0*	0.1	0.4	5.8**	0.8*	86.7**	13.3**	
		(0.32)	(0.23)	(0.46)	(0.42)	(0.28)	(0.59)	(0.5)	(0.23)	(0.29)	(1.19)	(0.41)	(2.20)	(2.20)
TO	77.6**	72.8**	81.8**	16.3**	38.4**	48.3**	35.0**	5.4**	45.7**	41.6**	31.3**	11.7**	**	
		(4.88)	(3.84)	(4.45)	(2.81)	(3.72)	(3.42)	(3.1)	(1.03)	(3.40)	(3.43)	(3.32)	(1.94)	**
NET	25.3**	13.4**	23.3**	−18.3**	−9.7**	−2.4	−12.8**	−6.4**	−2.5	−2.3	−5.8	−1.6	42.2**	
		(5.32)	(4.10)	(4.81)	(3.84)	(3.21)	(3.08)	(2.7)	(1.88)	(3.31)	(3.54)	(3.07)	(2.58)	(1.02)

Notes: See the footnote in Table 7.1.

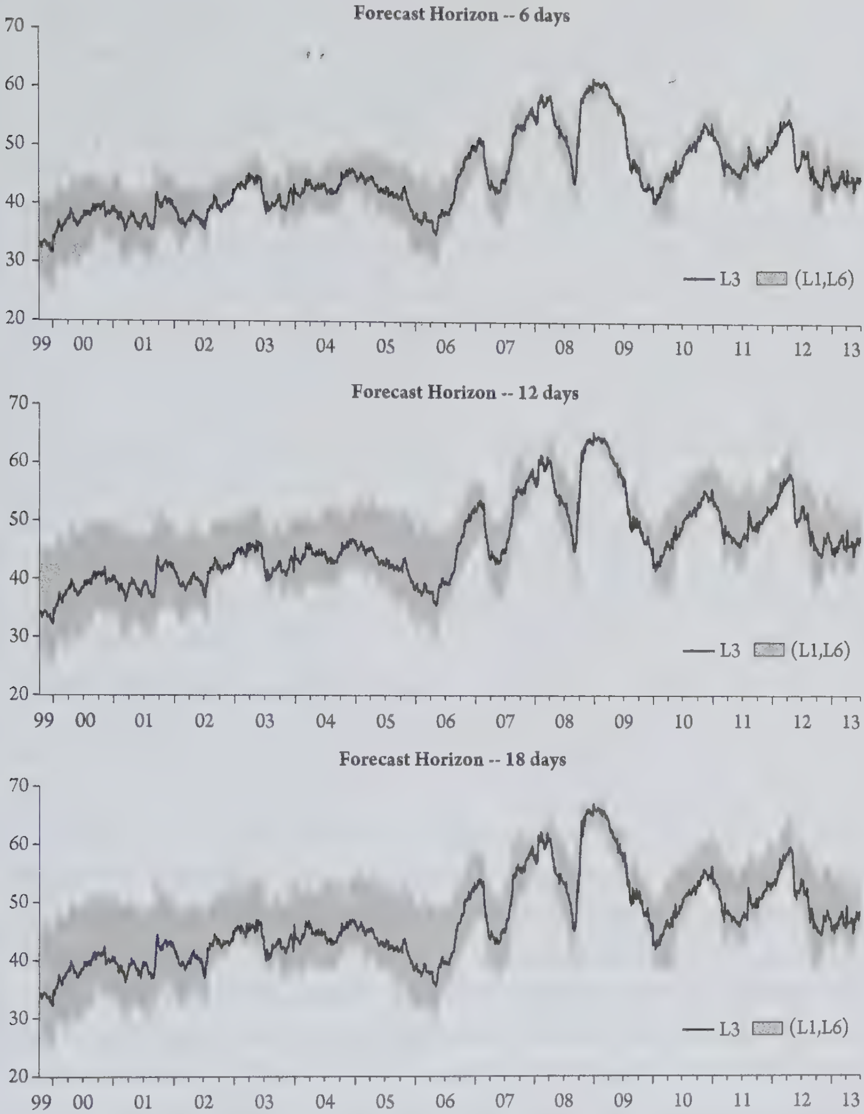


Figure 7.A.1 Robustness to forecast horizon and lag choice, total volatility connectedness across assets and countries (200-day window).
See the caption of Figure 2.A.1.

8

GLOBAL BUSINESS CYCLES

What started in the United States as the sub-prime mortgage crisis in 2007 later transformed into a severe global financial crisis that affected all major advanced and emerging economies. Indeed, the industrial countries experienced the worst recession in decades. As expected, the global recession increased academic and policy interest in business cycle research. In light of this interest, we decided to devote the last chapter of the book to the connectedness of business cycles among the leading economies of the world.

The academic literature on international business cycles dates back to the early 1990s. Since then, research on business cycles across countries has displayed ample evidence that macroeconomic fluctuations in industrial and developing countries have a lot in common. Using pairwise correlations of GDP, Backus et al. (1995) and Baxter (1995) showed that output in major industrial countries follow similar short-run paths. Employing a Bayesian dynamic latent factor model, Kose et al. (2003) found strong support for a persistent common factor that drives business cycles in 60 countries around the world. In a recent paper, using a multicountry Bayesian VAR model with time variations, Canova et al. (2007) also found evidence in favor of world business cycles among the G-7 countries. They also showed that the world- and country-specific fluctuations are more synchronized in contractions than in expansions.[1]

As the evidence on international business cycles accumulated, the literature started to focus on the effect of globalization on international business cycles. Kose et al. (2003) found that with increased globalization, the impact of the world factor on the correlation of macroeconomic aggregates (output, consumption, and investment) across countries increased in the 1990s and after. More recently, Kose et al. (2008) extended their previous findings to the second moments of output, consumption, and investment. Doyle and Faust (2005), on the other hand, found no evidence of increased correlation of growth rates of output in the United States and in other G-7 countries over time. Stock and Watson (2005) showed that the co-movement of macroeconomic aggregates has declined in the globalization era of 1984–2002. However, rather than linking their results directly to the globalization process, Stock and Watson (2005) concluded that their results are likely due to the diminished importance of common shocks among the G-7 countries. Eickmeier (2007) emphasized that the impact of globalization on international propagation of macroeconomic shocks is unclear and needs to be studied further.

In this chapter, we apply the connectedness index methodology to the seasonally adjusted monthly industrial production indices for the G-6 countries (excluding Canada from the G-7 group). The time variation in connectedness is potentially of great interest as the intensity of business cycle connectedness is likely to vary over time. Using a rolling windows approach and calculating the connectedness index for each window, we allow the business cycle connectedness across the G-6 countries to vary over time since 1958.

The connectedness index approach is different from earlier studies of international business cycles, in that, rather than finding a common world factor or indicator that measures international business cycles, this approach helps one identify how shocks to industrial production in one country affect the industrial output in other countries with some lag. Obviously, one is likely to find evidence for international business cycles if the shocks are common and/or if country-specific shocks are transmitted across countries in a statistically meaningful manner. Unlike the previous contributions to the literature, the connectedness index methodology also allows one to identify directional connectedness transmitted from one country to others, as well as the connectedness across country pairs (see Diebold and Yilmaz (2010)).

[1] In addition, empirical studies employing time series and spectral methods also find support for the presence of international business cycles (see Gregory et al. (1997) and Lumsdaine and Prasad (2003).)

Finally, the analysis of the present chapter differs from the majority of earlier contributions to the literature in terms of the data used. We use industrial production indices at monthly frequency rather than the quarterly data from the national income accounts. There are two reasons for this choice. First, the use of monthly data allows us to capture the connectedness of business cycle shocks much faster, as seen in the latest economic crisis. Second, the use of monthly data allows us to have more observations in calculating the connectedness index for each rolling sample window.

8.1 DATA, UNIT ROOTS, AND CO-INTEGRATION

To study the business cycle connectedness, we use monthly observations of the seasonally adjusted industrial production (IP) indices from January 1958 to October 2011.[2] Even though it is one of the G-7 countries, Canada is not included in the analysis, because the Canadian IP is highly correlated with the IP of the United States.[3]

Before going ahead with the analysis of business cycle connectedness, we first test whether the seasonally adjusted industrial production series for the G-6 countries are stationary or not. We use the most-preferred augmented Dickey–Fuller (ADF) test for this purpose. Test results for the whole period (1958:01–2011:12) are presented in Table 8.1. For all G-6 countries, the augmented ADF test fails to reject the null hypothesis that the log of the IP series (allowed to have a constant and a linear trend term) possesses a unit root at the 5% level of significance. This result obviously implies that none of the six IP series are stationary in levels. Applying the tests to the first-differenced log IP series, however, we reject the nonstationarity of this series for all six countries at the 1% level of significance. Together these results indicate that all IP series included in the analysis are integrated of order one, $I(1)$.

Once we show that all industrial production indices in the sample possess a unit root, we then test for the presence of a co-integration relationship among these six series. Johansen co-integration test results (both trace and maximum eigenvalue tests) show that there is a single co-integration relationship among the seasonally adjusted IP series for the G-6 countries over the 1958:01–2011:12 sample (see Table 8.2). Altogether, test results imply that, instead of estimating a VAR model in first differences (DVAR), one needs to estimate a vector error correction model with one

[2] Logarithms of industrial production series are plotted in Figure 8.A.1.

[3] Year-on-year industrial production growth rates for the two countries have a correlation coefficient of almost 87.1%, much higher than the correlation coefficients for other country pairs. Similarly, the correlation coefficient between the monthly IP industrial production growth rates of the two countries is equal to 39.9%, a value much higher than the ones for other pairs of countries (see Table 8.A.1). Artis et al. (1997) show that with a value of 85.6% the contingency correlation coefficient between the U.S. and Canadian industrial production is the highest among the G-7 countries.

Table 8.1 Unit Root Test—G-6 Industrial Production (1958:01–2011:12)

Augmented Dickey–Fuller Test Statistics						
	USA	*Germany*	*Japan*	*France*	*UK*	*Italy*
Log levels	–2.95	–4.12	–1.45	–0.95	–0.63	–0.71
Log first difference	–7.50	–12.00	–14.91	–23.79	–30.82	–33.46

Critical Values—Augmented Dickey–Fuller Test			
	1%	*5%*	*10%*
Log levels	–3.972	–3.417	–3.131
Log first difference	–3.440	–2.866	–2.569

Notes: In applying the augmented Dickey–Fuller test to log industrial production, we include a constant term and a trend, but only a constant term in the case of first differences of log industrial production. Critical values for the augmented Dickey–Fuller test are provided in the lower part of the table at the 1%, 5%, and 10% level of significance.

co-integration equation (VEC1), which is effectively a DVAR which includes the first lag of the error correction term from the co-integration equation.

8.2 THE EMPIRICS OF BUSINESS CYCLE CONNECTEDNESS

8.2.1 The Business Cycle Connectedness Table

In the empirical analysis of business cycle connectedness, we first estimate the VEC1 model (with three lags) for the full sample and report the connectedness index and the directional connectedness in Table 8.3 along with the underlying generalized variance decomposition over a 12-month forecast horizon. The connectedness index for the full sample period is 38.8%, indicating that less than one-third of the total variance of the forecast errors for the G-6 countries is explained by the connectedness of shocks across countries, whereas the remaining 71.2% is explained by idiosyncratic shocks.

It is important at this stage to note that the connectedness index for the whole sample is very sensitive to the inclusion of new observations in the sample. The connectedness index for the period from 1958:01 to 2008:12 is only 27%. When the sample is extended to May 2009, the connectedness index for the full sample jumps to 69%. Finally, the inclusion of observations from June 2009 to October 2011 lowers the index to 28.8%.

In terms of the directional connectedness to others (measured by $\tilde{C}^{H}_{\bullet\leftarrow i}$) throughout the full sample, Japan is the country that contributed the most to other

Table 8.2 Johansen Co-integration Rank Test—G-6 Industrial Production (1958:01–2011:12)

Trace Test Statistic				
Hypothesized No. of CE(s)	*Eigenvalue*	*Trace Statistic*	*Critical Value (0.05)*	*P-Value*
None**	0.0733	115.6	95.8	0.0011
At most 1	**0.0442**	**66.7**	**69.8**	**0.0865**
At most 2	0.0267	37.6	47.9	0.3191
At most 3	0.0226	20.3	29.8	0.4054
At most 4	0.0084	5.6	15.5	0.7473
At most 5	0.0001	0.12	3.8	0.7230

Maximum Eigenvalue Test Statistic			
Hypothesized No. of CE(s)	*Maximum Eigenvalue Statistic*	*Critical Value (0.05)*	*P-Value*
None**	48.9	40.1	0.004
At most 1	**29.1**	**33.9**	**0.168**
At most 2	17.4	27.6	0.550
At most 3	14.7	21.1	0.310
At most 4	5.4	14.3	0.687
At most 5	0.12	3.8	0.723

Notes: We assume that there is a linear deterministic trend in the data and an intercept in the cointegrating equation (CE); ** denotes rejection of the hypothesis at the 1% level.

Table 8.3 Business Cycle Connectedness—G-6 Countries (1958:01–2011:12)

	USA	*GER*	*JPN*	*FRA*	*UK*	*ITA*	*FROM*
USA	89.2	0.8	3.5	3.3	2.2	1.1	10.8
Germany	5.6	55.7	23.9	8.4	6.0	0.5	44.3
Japan	8.1	5.6	77.4	6.0	1.9	1.0	22.6
France	3.5	10.1	11.0	64.2	4.2	7.0	35.8
UK	7.7	3.3	4.2	3.8	80.0	1.0	20.0
Italy	5.9	2.0	14.3	13.2	4.0	60.6	39.4
TO	30.9	21.7	56.8	34.7	18.3	10.5	
NET	20.0	–22.5	34.1	–1.1	–1.7	–28.8	**28.8**

countries' forecast error variance (56.8 percentage points, which is close to 10% of the total forecast error variance to be explained), followed by France (34.7 percentage points). According to the full sample directional connectedness measures, the United States, Germany, and the United Kingdom contributed at similar rates (30.9, 21.7, and 18.3 points, respectively), followed by Italy (10.5 percentage points).

In terms of the directional connectedness received from others (measured by $\tilde{C}^H_{i\leftarrow\bullet}$), the United Kingdom appears to be the country that received the lowest percentage of shocks from other countries (10.8 points, equivalent to just 1.8% of the total forecast error variance to be explained) followed by the United Kingdom (20 points) and Japan (22.6 points). Germany received the highest percentage (44.3 points) of shocks from other countries, followed by Italy (39.4 points) and France (35.8 points).

Finally, we calculate the difference between the column-wise sum (what is called the "contribution from others") and the row-wise sum (called the "contribution to others") to obtain the "net directional connectedness" given by $\tilde{C}^H_i$. Japan (34.1 percentage points) and the United States (20.1 percentage points) are net transmitters of industrial production shocks to other countries, while the United Kingdom (–1.1 percentage points) and France (–1.7 percentage points) received very low percentage of business cycle shocks in net terms. Italy (–28.8 points) and Germany (–22.5 points), on the other hand, are definitely the leading net recipients of business cycle shocks over the full sample.

8.2.2 The Business Cycle Connectedness Plot

The connectedness table for the full sample provided us with important information for the static connectedness analysis. However, as emphasized in the introduction, the focus of the chapter is more on the dynamics of business cycle connectedness over time. The fact that the inclusion of new observations in the sample leads to significant jumps in the connectedness index definitely highlights the need to study the dynamics of connectedness over time.

As the VEC is the correct model for the full sample, the dynamic analysis of connectedness also relies on the variance decomposition from the VEC1 model estimated over rolling 5-year windows. Here is how the connectedness plot is obtained: We estimate the VEC1 model for the first 5-year sub-sample window (April 1958–April 1963) and obtain the value for the generalized variance decomposition-based connectedness index (from now on, the connectedness index). Moving the sub-sample window one month ahead, we estimate the VEC1 model again and calculate the connectedness index for the new sub-sample and so on. Graphing the connectedness index values for all sub-sample windows leads to the connectedness plot.

So far we have discussed the connectedness plot based on the underlying VEC1 model, estimated over 5-year rolling windows with a 12-month forecast horizon. Next we want to discuss the appropriateness of our assumptions and the robustness of our results to these assumptions. Let's start with the underlying VEC1 model. In Tables 8.1 and 8.2 we reported unit root and co-integration test results for the full sample from 1958:01 to 2011:12. While the test results indicated that the correct underlying model is the VEC1 for the full sample, this does not necessarily imply that VEC1 is the correct model for each 5-year rolling window. For that reason, we repeat the unit root and co-integration tests for all 5-year rolling windows considered. The *p*-values for ADF unit root tests for the log IP series in levels and in first differences are respectively presented in Figures 8.A.2 and 8.A.3, both in the appendix to this chapter. The dotted straight line in each graph indicates the 5% level. The ADF test fails to reject the presence of unit roots in the log IP series for an overwhelming majority of the windows considered for all countries. In the case of first-differenced log IP series, the ADF test rejects the presence of unit roots for almost all countries. The only exception is Japan. In the case of Japan, for a non-negligible number of rolling windows the ADF test fails to reject the presence of unit roots in the first-differenced log IP series. While this is a cause for concern, we do not test for unit roots in further differenced IP series. Instead, we proceed with the Johansen co-integration test over the rolling windows. In the case of the United Kingdom, the ADF test rejects the unit root in the first-differenced log IP series so strongly for all windows that the *p*-value is very close to zero.

The Johansen's trace and maximum eigenvalue co-integration test results are presented in this chapter's appendix, in Figures 8.A.4 and 8.A.5. Both trace and maximum test statistics reject the null of no co-integration relationship among the six log IP series at the 5% level for an overwhelming majority of rolling windows considered. This means that the test prefers a VEC1 model to a DVAR model. In contrast, the trace statistic, in particular, fails to reject the null of at most one co-integration equation linking all six log IP series. Therefore, the Johansen co-integration tests indicate that there is either one or two co-integration equations among the six IP series. Based on these results, we expand the connectedness index analysis to rolling windows based on the VEC1 model. Later on, we will show the differences in the connectedness indices for different models.

The dynamic connectedness index based on the VEC1 model is plotted in Figure 8.1. We also calculate an alternative connectedness index based on the Cholesky variance decomposition. Even though we do not plot it here, we can report that the two indices move in tandem, with the difference between the two indices seldom exceeding 10 percentage points. Therefore, it would be sufficient to focus on the generalized VD-based connectedness index for the rest of the chapter.

Turning to Figure 8.1, the first thing one observes about the connectedness plot is the absence of a long-run trend. The connectedness plot clearly shows that while there

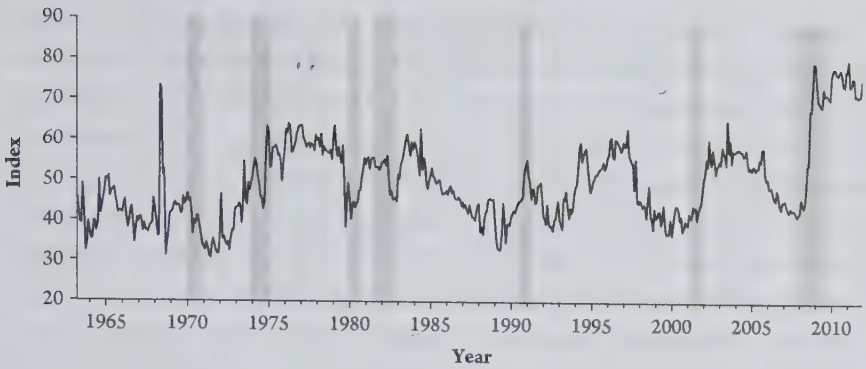


Figure 8.1 Total business cycle connectedness—G-6 countries (1958:01–2011:12). Gray-shaded bars indicate U.S. recession periods.

are periods during which shocks to industrial production are substantially transmitted to others, there are yet other periods during which the connectedness of business cycle shocks was much less important. Actually, during or after all U.S. recessions (indicated by the shaded bars in Figure 8.1), the connectedness index recorded significant upward movements. The only exception is the 1969–1970 recession, during which the index moved down. In addition, the index went up in late 1993, and after a brief correction in late 1994, it went up again in 1995. While there was no U.S. recession during this period, France, Germany, Italy, and Japan experienced recessions ending in late 1993 or early 1994 (see the Economic Cycles Research Institute's website http://www.businesscycle.com/resources/cycles/). As a result, the upward movement in the connectedness index is most likely due to the connectedness originating from these countries.

Second, while the connectedness index fluctuates over time, it is possible to differentiate between several trends. First, during the 1973–1975 recession the connectedness index increased by almost 20–25 percentage points and fluctuated around 50% after the 1981–1982 recession. Starting in 1984, the connectedness index declined all the way to 33%. This result is consistent with the findings of McConnell and Perez-Quiros (2000) and Blanchard and Simon (2001) that the volatility of the U.S. GDP declined after 1984 (the great moderation). As the volatility of GDP declines, the connectedness index declines to pre-1973 levels.

Third, after the great moderation of the late 1980s, the behavior of the connectedness index reflected the influence of globalization. From 1989 onward, the band within which the connectedness index fluctuates started to move upward with the current wave of globalization that started in earnest in the early 1990s. As the sample windows are rolled to include 1996, the index reaches 60%, but declines to 40% as the data for the late 1990s and 2000 are included. The index starts to increase again toward the end of the mild recession of 2000–2001, reaching 60% by the end of 2002.

However, as the other G-6 countries followed the quickly recovering U.S. economy to a major expansion, the connectedness index reached 65% in the second quarter of 2004. The index then declines to 60% again as the window is rolled to include the second half of 2004 and then gradually moves down, reaching its bottom around 40% from the last quarter of 2006 until the first quarter of 2008.

During the era of globalization, from the late 1980s to 2007, the connectedness index followed three distinct cycles. Each cycle lasted longer and had a larger bandwidth than the previous one. During the first cycle, which lasted from 1989 to the end of 1992, the index fluctuated between 33% and 53%, while in the second cycle, which lasted from 1993 to 1999, the index fluctuated between 37% and 60%. Finally, during the third cycle from 2001 to 2007, the index fluctuated between 44% and 65%.

This result is consistent with Kose et al.'s (2003) finding that with the globalization process, business cycles have become more synchronized. It basically indicates that the co-movement of industrial production fluctuations has tended to be more significant since the late 1980s. In other words, when there is a shock to industrial production in one or more countries in the G-6 group, its tendency to be transmitted across other countries increases as one moves from 1989 toward 2007. This result can also be interpreted as consistent with Doyle and Faust's (2005) conclusion that the correlation coefficients among the industrial production series have not increased much since the late 1980s. The output fluctuations tend to move together during periods of high connectedness indices, compared to the periods with low connectedness indices. When one analyzes the period since the late 1980s as a whole, one may not obtain high correlation coefficients. Actually, for the period from 1989 to 2007 the connectedness index is only 36%.

Next, we focus on the behavior of the connectedness index since June 2008 (see Figure 8.2). We want to focus on its most recent behavior, not only because it provides us with more clues about the business cycle connectedness since the beginning of the

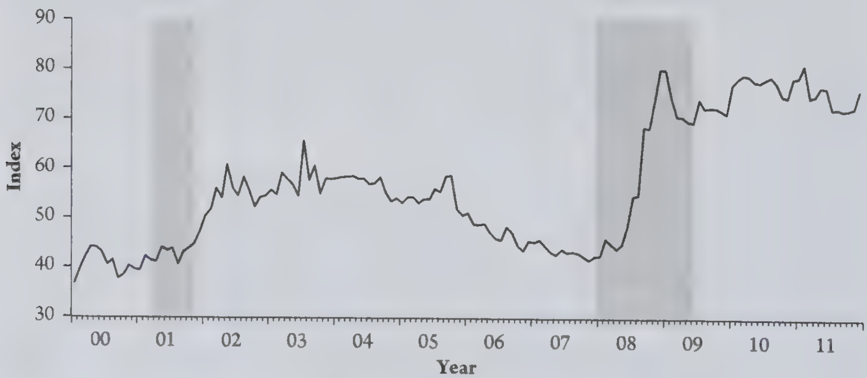


Figure 8.2 Total business cycle connectedness—G-6 countries (2000:01–2011:12). Gray-shaded bars indicate U.S. recession periods.

sub-prime crisis in the United States, but also because, in 2008 and 2009, the index recorded the biggest jump in its history. The index increased sharply from 41% in May 2008 to 53% in July, to 68% in September, and then to 80% in December 2008. With the inclusion of January 2009 through October 2009 in the analysis, the index declined slightly to 71%. As the economic recovery was underway in the G-6 countries in the second half of 2009, the index moved slightly upward again, reaching 75% by December 2009.

The behavior of the index during the Great Recession of 2007–2009 is in stark contrast to its behavior in previous recessions. It increased 37 points from April to December 2008. The jump in the index during the Great Recession is an indication of how the G-6 countries were pulling each other down. To give an example, during the recession following the first oil price hikes, in a matter of three and a half years from 1972 to 1976, the connectedness index recorded a relatively smaller increase, from a low of 32 in August 1972 to a high of 64 in April 1974.

8.2.3 Sensitivity Analysis

So far we have only discussed the total business cycle connectedness index. However, as we argued in the introduction to this chapter, the analysis of directional connectedness provides us with quite interesting results to discuss in some detail. However, before going ahead with the analysis of directional connectedness plots, we want to make sure that the total connectedness analysis results are not due to some special characteristics of the VEC framework we use. For that reason, we now report the robustness of the total connectedness index with respect to the model choice, the window width, the forecasting horizon, and the ordering of variables.

Let's start the sensitivity analysis with the underlying model. Along with the VEC1 (single co-integration equation) model, we calculated the total connectedness index under DVAR, VEC2, and VEC5 models. We present the dynamic connectedness plots for the DVAR, VEC2, and VEC5 models in Figures 8.3(a), 8.3(b), and 8.3(c), along with the connectedness index obtained using the VEC1 model. As can be seen from Figure 8.3(a), the dynamic connectedness plot obtained from the underlying DVAR model differs substantially from the one obtained from the VEC1 model. Given the fact that the null hypothesis of no co-integration equation was very strongly rejected by Johansen's co-integration test using both trace and maximum eigenvalue statistics, it is not very surprising that the dynamic connectedness index obtained from the DVAR model is very much different from the one obtained with the VEC1 model (see Figure 8.3(a)).

Co-integration test results, in general, preferred the VEC1 model to the VEC2 and VEC5 models, but there were many instances, especially in the case of maximum eigenvalue statistics, where the null of at most one cointegration equation was

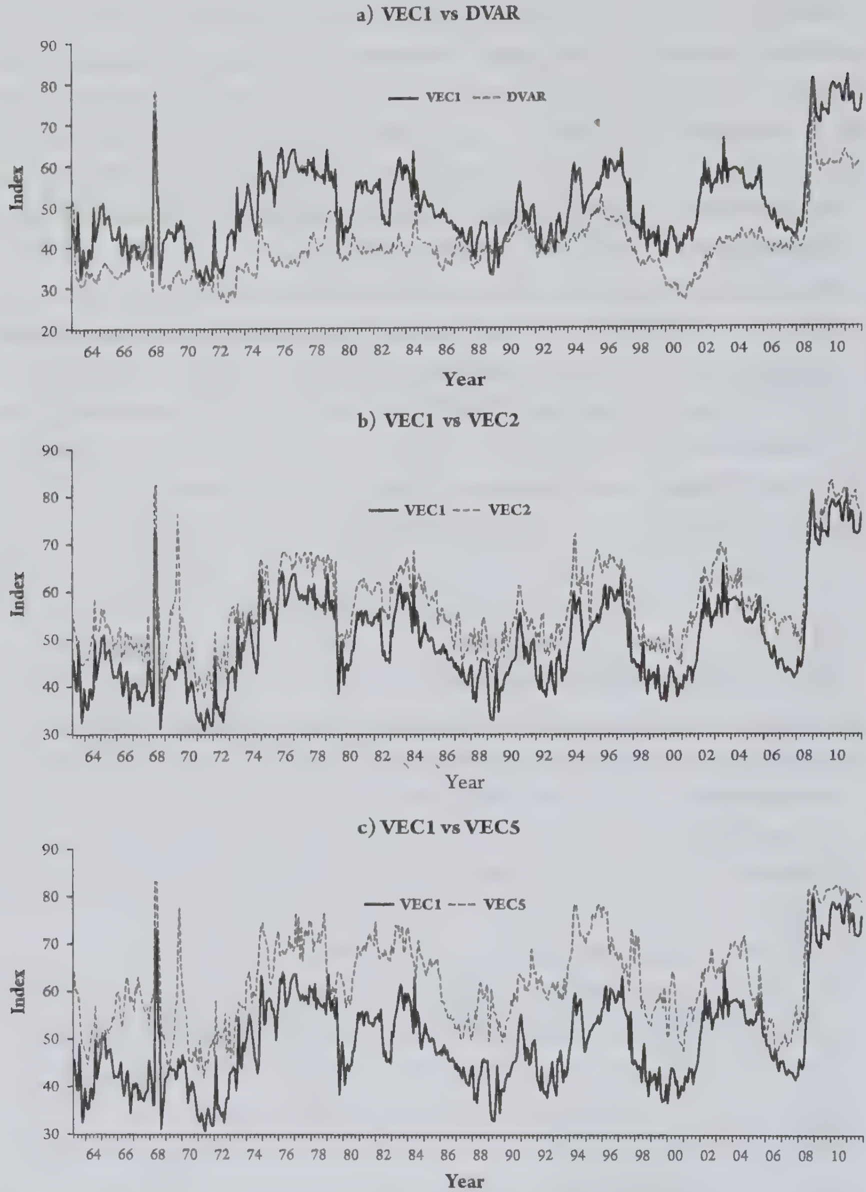


Figure 8.3 Business cycle connectedness and the underlying model—G-6 countries.

rejected in favor of two or more co-integration equations (see Figures 8.A.4 and 8.A.5 in this chapter's appendix). Given that the Johansen test results did not indicate an overwhelming preference in favor of the VEC1 model, we decided to compare the behavior of the total connectedness index from the underlying VEC1 model with the ones obtained from the VEC2 and VEC5 models. As can be seen from Figures 8.3(b) and 8.3(c), there is a level difference between the connectedness index obtained from the VEC1 model and the ones obtained from the VEC2 and VEC5 models. As the level difference is not changing substantially over time, there is little difference between the time behavior of the VEC1-based connectedness index and the ones obtained from the VEC2 and VEC5 models. Based on these results, we decided to use the VEC1 as the main underlying model.

Next, we present the robustness checks with respect to the window width and the forecast horizon in Figure 8.4. In this robustness exercise we consider 4, 6, and 7 years as the alternatives to our benchmark window width of 5 years. In the case of the forecast horizon, we consider 6 and 18 months in addition to our benchmark forecast horizon of 12 months. In total, we plot the dynamic connectedness index in 12 subgraphs. In addition to the connectedness index, which is based on generalized variance decomposition, we plot the 10th and 90th percentile values of the Cholesky-based connectedness index out of 100 random orderings.

Irrespective of the forecast horizon and window width considered, the generalized and Cholesky variance decomposition-based connectedness indices follow very similar patterns. This comparison assures us that the use of the generalized variance decomposition-based connectedness index leads to quite sensible results. Figure 8.4 also assures us that the result we obtained for the benchmark values of the window width and the forecast horizon carries over when we use other values for these two important parameters of our connectedness index methodology.

8.2.4 The Dynamics of Directional Business Cycle Connectedness

Following the analysis of the total connectedness index, we can now focus on the directional connectedness of business cycles across countries. Directional connectedness indices are critical in understanding the respective roles of each of the G-6 countries in spreading shocks to their local industrial outputs to other countries. In Figure 8.5 we present all three indices of connectedness: "Connectedness to others," "Connectedness from others," and "Net connectedness to others," which we will discuss in some detail.

Throughout the 1970s, Japan was the most important source country of net connectedness (Figure 8.5), followed by France and Germany. During the second half of the 1970s, the gross connectedness from Japan to others reached as high as 180%, whereas the connectedness received by Japan from others was only around 40–50%, leading the net connectedness from Japan to reach as high as 150% (Figure 8.5). While Germany had high directional connectedness to others in the late 1960s, early 1970s, and late 1970s, its net connectedness was negative in the mid1970s, immediately after the first oil price shock. In contrast, France had significant directional connectedness to others after the first oil price hikes in 1973–1974 as well as the second half of the 1970s. The United States, on the other hand, had negative

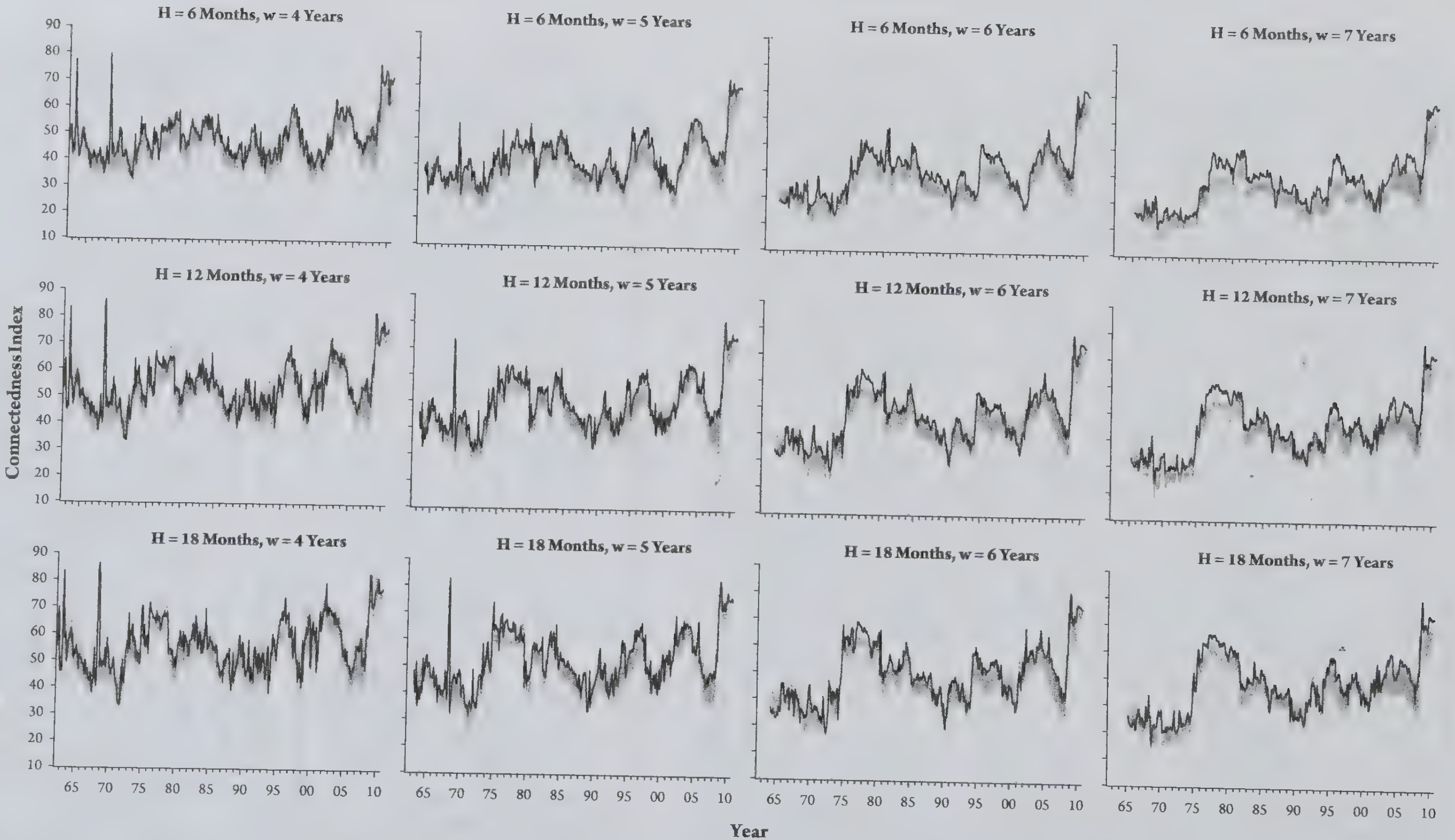


Figure 8.4 Robustness with respect to window width, forecast horizon, and ordering of variables.

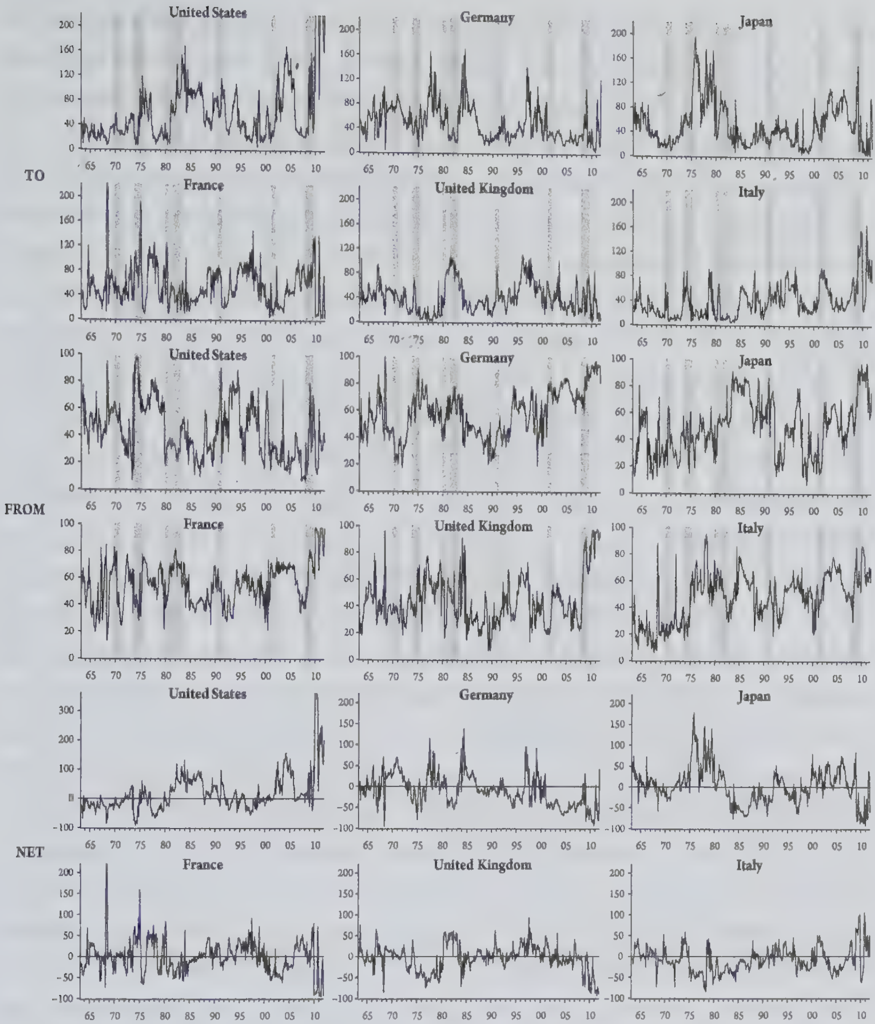


Figure 8.5 Directional business cycle connectedness—G-6 countries (1958:01–2011:12). Gray-shaded bars indicate U.S. recession periods.

directional connectedness to others, therefore, it was a net recipient of business cycle shocks over most of the 1970s.

The roles were reversed in the 1980s: The United States became the major net transmitter of shocks, while Japan became the net recipient of the business cycle shocks. Following the 1981–1982 U.S. recession, gross connectedness transmitted by the United States to others jumped above 160%, and net connectedness from the United States fluctuated between 50% and 120% (see Figure 8.5). Japan's net connectedness, on the other hand, declined to as low as –80% after the 1982 recession and stayed at low levels until the end of 1987. Indeed, as can be seen in Figure 8.A.6, the bulk of the increase in the United States' net business cycle connectedness in 1980s was due to the increase in its pairwise connectedness with Japan. Germany and the United Kingdom also had positive net directional connectedness to others after the 1981–1982 recession, but their roles were rather secondary compared to that of the United States (Figure 8.5).

Throughout the 1990s, Japan's net directional connectedness was positive, but it was rather low. This fact is consistent with the decade-long recession Japan suffered while the other G-6 countries continued to attain higher growth rates. Neither the United States nor Germany was one of the countries that had net directional connectedness in the 1990s. Rather, France and the United Kingdom had sizeable net directional connectedness in the 1990s, even though their net connectedness was not as significant and persistent as the ones the United States, Japan, and Germany attained in the 1970s and 1980s. The role these countries played during the 1990s is closely related to the aftermath of the ERM crisis of 1992 and the ensuing slowdown in these economies.

Moving forward in time, the United States and Japan returned to their locomotive roles in the 2000s. In particular, with a high net connectedness to others, the United States became a net transmitter of business cycle shocks after the 2001 recession. In response to the slowdown in the economy in early 2001, the Fed lowered the Fed funds rate from 5.5% in January 2001 all the way down to 2% in November 2001. This aggressive policy stance was effective in stimulating domestic demand. As a result, industrial production grew at a monthly rate of between 0.5% and 1.0% in the first half of 2002. The 2001 recession lasted for only 8 months, from March to November 2001. With this rapid turnaround, the United States started to generate substantial connectedness in the first half of 2002, with the net connectedness from the United States reaching 100%. After a brief lull in 2003, the net connectedness from the United States increased again to surpass 130%. Being the driver of worldwide demand, the United States had an impact on other countries until the end of 2006, as the net connectedness of the United States declined to almost zero. Japan also had a positive net connectedness in the first 7 years of the 2000s; its net connectedness fluctuated around 50%. Germany's net directional connectedness was negative throughout the 2000s and during the global recession of 2008–2009. France, Italy, and the United Kingdom were also net recipients of business cycle shocks before the global recession.

Lately, with a net connectedness measure lower than –50% since 2007, Japan has become a net recipient rather than a net transmitter of business cycle connectedness. In the meantime, the net connectedness from the United States has gradually increased with the intensification of the sub-prime crisis since mid-2007. As emphasized above, from April to December 2008, the total connectedness index jumped up substantially to reach 80%. The United States was the most important contributor to the increase in business cycle connectedness, with a net connectedness contribution of more than 150% (Figure 8.5). The gross directional connectedness from the

United States jumped close to 180% following the collapse of Lehman Brothers in September 2008.

While the United States was the major net transmitter of shocks to others, France and Italy had also become important net transmitters during the global recession of 2007–2009. Actually, the net connectedness of both countries stayed high after late 2008, fluctuating between 50% and 100%. According to Figure 8.5, since the global financial crisis, the net connectedness of Germany, the United Kingdom and Japan had declined rapidly, dropping all the way to –100% in early 2010.

8.3 INTERNATIONAL TRADE AND DIRECTIONAL CONNECTEDNESS

Germany has been the biggest economy and the manufacturing powerhouse of Europe. It is therefore not easy to reconcile the above result with the image of Germany as the engine of growth in the EU. Now, let's discuss the logic behind this result in some detail. Trade flows play a key role in the transmission of shocks across countries. When there is a shock to domestic demand in country *i*, this shock is transmitted to other countries through the trade channel. As the aggregate demand in country *i* takes the hit, the demand for imports is affected as well. As a result, the domestic shock is likely to be transmitted to other countries, which are major exporters country *i*.

As can be seen in Table 8.4, from 1999 to 2008, Germany's average trade surplus in manufacturing vis-à-vis the other five countries was equivalent to 6.5% of its industrial output. Over the same period the United Kingdom, the United States, and France ran manufacturing trade deficits, while Japan and Italy ran manufacturing trade surpluses vis-à-vis the other G-6 countries. Germany happens to be the most important exporter of manufacturing goods to France, the United Kingdom and Italy, and it ranks only second or third among exporters to the United States and Japan. As a result, when there is a negative shock to industrial production in one or more of the G-6 countries, this shock is likely to be transmitted, first and foremost, to Germany and then to the other countries. From this perspective, it is logical for Germany to have a higher connectedness from others compared to its connectedness to others.

In order to better understand the possible link between the trade balance and the business cycle connectedness, we undertake a linear regression analysis. In the regressions, the dependent variable is the natural logarithm of the ratio of the connectedness "to others" to the connectedness "from others" for the country in question ($C_{\bullet\leftarrow i}/C_{i\leftarrow\bullet}$). On the right-hand side, we include only the natural logarithm of the ratio of the country *i*'s total exports to total imports, with a lag of 12 months. Regression results for the full sample (1963:04–2010:02) as well as for the sub-sample that covers the period from January 1990 to the end of the sample are presented in Table 8.5.

Table 8.4 Bilateral Manufacturing Trade Balance Relative to Local Manufacturing Production (1999–2008, Average)

	United Kingdom	*Germany*	*Japan*	*France*	*United Kingdom*	*Italy*
United States	—	2.4	2.7	1.4	1.6	0.6
Germany	–0.6	—	0.1	–2.4	–5.0	–1.7
Japan	–1.2	–0.2	—	–0.1	–1.6	–0.1
France	–0.1	1.6	0.02	—	0.1	0.8
United Kingdom	–0.1	1.5	0.3	0.7	—	0.9
Italy	–0.2	1.1	0.02	–0.2	–1.2	—
Total	–2.0	6.5	3.1	–0.5	–6.1	0.5

Notes: Each cell shows the manufacturing trade balance of the column country with the row country, divided by the industrial production of the column country. For example, while Germany's manufacturing trade surplus vis-à-vis the United States is 2.4% of German industrial production, the corresponding U.S. manufacturing trade deficit vis-à-vis Germany is 0.6% of the U.S. industrial production.

Source: Authors' calculations based on OECD data.

Table 8.5 Trade Balance and the Directional Connectedness

	1963:04–2010:02		*1990:01–2010:02*	
	Coefficient	R^2	*Coefficient*	R^2
France	2.45	0.70	–4.95	0.80
	(2.91)		(4.36)	
Germany	–3.85	0.70	–6.31**	0.61
	(2.63)		(2.4)	
Italy	0.59	0.68	–4.10**	0.56
	(1.42)		(1.17)	
Japan	–1.16	0.75	–6.98**	0.74
	(1.34)		(2.46)	
United Kingdom	6.43*	0.74	6.46^{+}	0.71
	(2.61)		(3.45)	
United States	–1.76**	0.76	–2.59**	0.63
	(0.49)		(0.91)	

Notes: The dependent variable is $\ln(C_{\bullet\leftarrow i}/C_{i\leftarrow\bullet})_t$, and the explanatory variable is $\ln(\mathrm{exp}/\mathrm{imp})_{t-12}$.

The results for the full sample (1963:04–2010:02) are not encouraging. Only the United States has a statistically and economically meaningful coefficient estimate with the expected negative sign. The estimated coefficient implies that when the ratio of one-year lagged U.S. exports to U.S. imports increases by 1%, the ratio of the connectedness from the United States to the connectedness received by the United States will decline by 1.76%. The estimated coefficient for the United Kingdom (6.43) is also statistically significant, and its positive sign implies that a decrease in the export–import ratio will lead to a decrease in the connectedness from the United Kingdom relative to the connectedness received by the United Kingdom.

With the globalization process underway, trade flows became more and more important in the 1990s. Therefore, it makes sense to focus on the recent decades. For that reason, we restrict the sample to the post-1990 period. Five out of six estimated coefficients for the post-1990 period had negative signs as expected. For four of these countries (France is the exception), the negative coefficient estimates are statistically different from zero at the 1% significance level. The estimated elasticity for the United Kingdom is still positive, but it is different from zero at the 10% level of significance only.[4]

8.4 ALTERNATIVE MEASURES: COUNTRY FACTORS

In order to check for the robustness of our results obtained from the industrial production indices, in this short section we use a set of alternative measures of the behavior of each of the G-7 economies over the business cycle. Recently, using data on major macroeconomic variables at monthly and quarterly frequency, Aruoba et al. (2011) estimated dynamic factor models for the G-7 countries and derived country factors for each of the countries using 37 monthly indicators. Aruoba et al. (2011) showed that the country factors captured the main macroeconomic developments over a period of 40 years and that their behavior over time were fairly consistent with the business cycle narrative for each of the countries.

Applying the connectedness methodology to monthly country factors obtained by Aruoba et al. (2011), we calculated the total connectedness index for different window lengths. In Figure 8.6 we present the total connectedness index obtained from a VAR

[4] The United Kingdom runs chronic deficits in merchandise trade, which is financed by chronic trade surpluses in services. Being a deficit country in merchandise trade the United Kingdom is likely to be a net transmitter of shocks to other countries. However, given the large size of its trade surplus in services (service exports revenue reached $249 billion in 2009 compared to $117 billion in merchandise exports), the United Kingdom is likely to be a net receiver of shocks in services sectors from other countries. As a result, when we regress the log of the ratio of connectedness transmitted and received by the United Kingdom on the log of the export–import ratio for goods, the coefficient turns out to be positive but statistically insignificant.

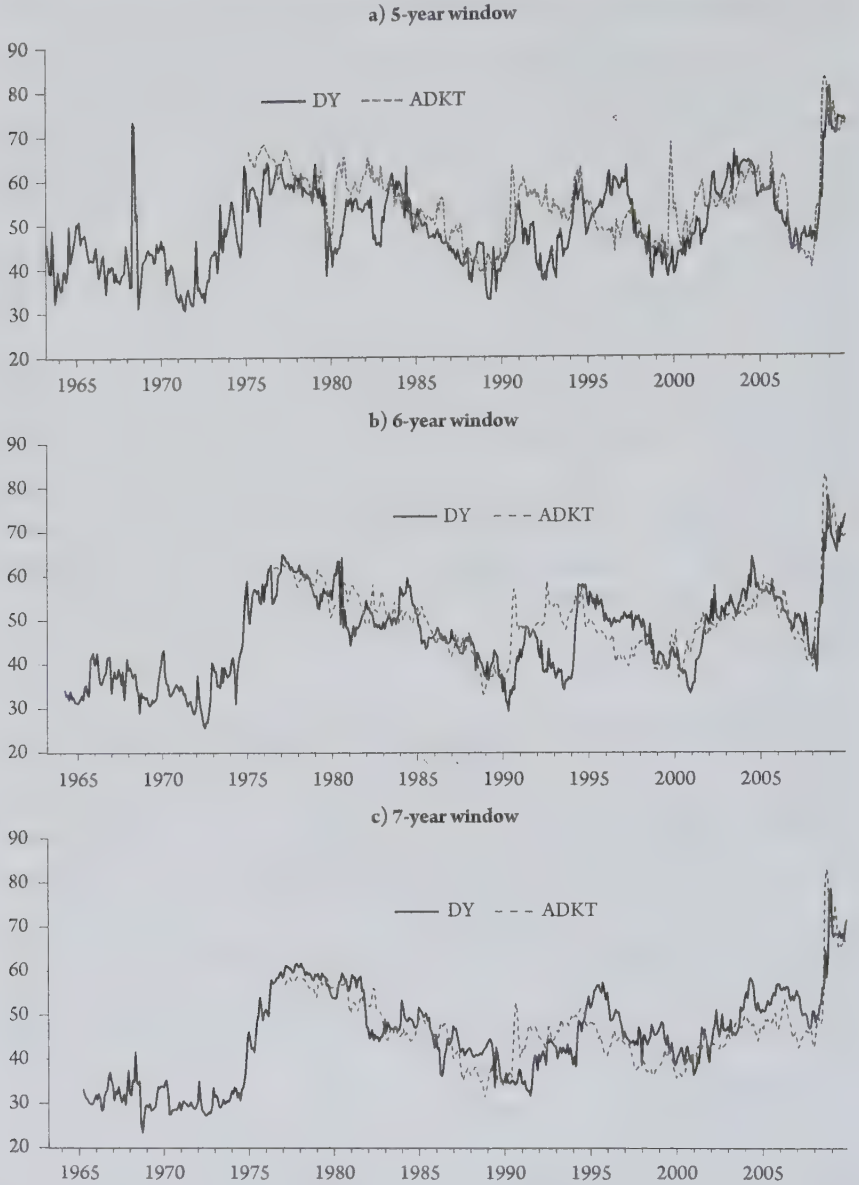


Figure 8.6 Business cycle connectedness—G-6 countries: Country factors (ADKT) versus industrial production (DY).

of the country factors over a sample window of 5 years through 7 years, along with total connectedness indices obtained from the VEC1 model of monthly industrial production indices.

When we use 5-year and 6-year rolling windows to calculate the connectedness index, the behavior of the country-factor- and industrial-production-based connectedness indices are quite similar. In the case of the 7-year window, there is a level difference between the two indices. The industrial-production-based index tends to be higher than the country-factor-based index. Despite that level difference, however, the two indices behave quite similarly over time. Based on Figure 8.6, we can conclude that the connectedness of business cycles across the G-6 countries are well captured by the use of industrial production data.

8.5 THE ANALYSIS WITH BRIC COUNTRIES

From the beginning, we included only six major industrial countries in the analysis of business cycle connectedness. As of the early 1990s, these countries accounted for slightly more than half of the world GDP measured in purchasing power parity. However, the 1990s and especially the 2000s witnessed the gradual integration of developing countries (what are now called emerging market economies) into the world economy. Four of the emerging market economies, namely, Brazil, Russia, India, and China, grew rapidly in the 2000s and increased their share of world GDP. While the BRIC countries accounted for approximately 14% of the world GDP in the early 1990s, by 2009 they had increased their share to 23.5%. According to the projections reported in the IMF's World Economic Outlook, their share of world GDP is expected to increase to 29% by 2015.

Given the rapid rise of China and other BRIC countries on the world stage, we thought it would be appropriate to include these countries in our analysis and to see whether our total and directional connectedness measures look different when we include them. Without dropping any of the G-6 countries, we report the results of the connectedness analysis with 10 countries in the VEC1 model.

We present the total, the net directional and the pairwise directional connectedness plots in Figures 8.7, 8.8 and 8.A.7. As can be observed, the overall trajectory of

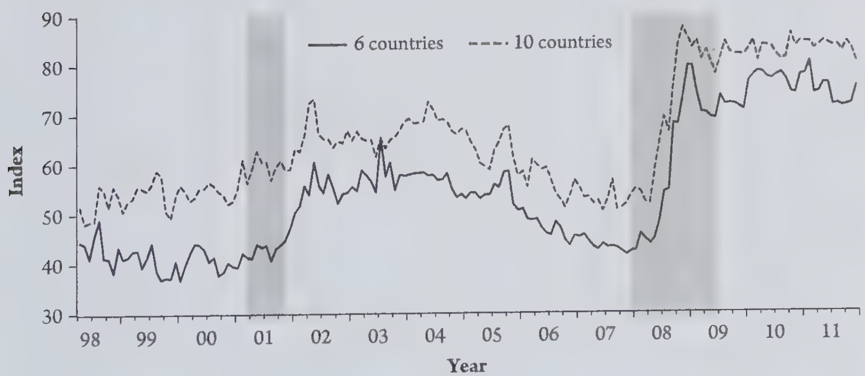


Figure 8.7 Business cycle connectedness—G-6 and BRIC countries (1993:01–2011:12). Gray-shaded bars indicate U.S. recession periods.

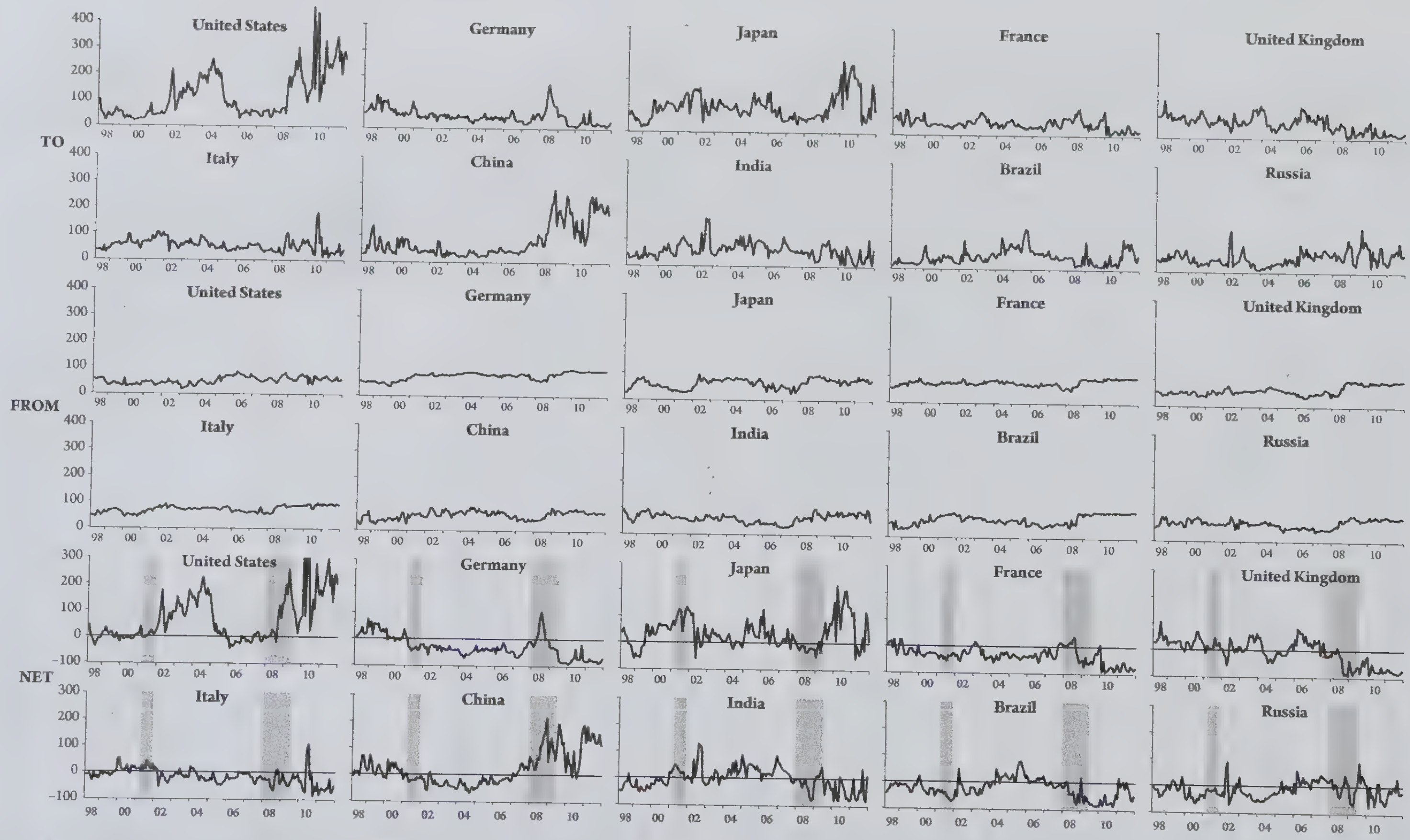


Figure 8.8 Directional business cycle connectedness—G-6 and BRIC countries (2000:01–2011:12). Gray-shaded bars indicate U.S. recession periods.

the total connectedness index is not affected from the inclusion of the BRICs in the sample. The fact that it is almost everywhere higher when we include the BRICs is not surprising. Since there are more countries in the sample, we would expect the connectedness to be higher. The difference is larger for the late 1990s, the early 2000s, and throughout 2006–2007.

The directional connectedness plots are more significantly affected from the inclusion of the BRICs. First, over the 2002–2004 and the 2008–2010 periods, the net connectedness of the United States to others increases to, and even surpasses, 200% compared to its level in the 100%–120% range when only G-6 countries are included. The net connectedness of the United States reaches 200% and stays high during the recession of 2007–2009. After a brief respite in the second half of 2009, the United States started generating significant connectedness in 2010 again, with its net connectedness reaching 250%.

Unlike the case in the six-country analysis, in the 10-country analysis Japan has positive net connectedness in 2009 and 2010. Its net connectedness increased from –80% to 100% in mid-2009, and then it fluctuated in the positive territory until the end of 2010. Following the earthquake in March 2011, Japan's net connectedness moved to the negative territory again.

The results for Germany and the United Kingdom are not much different from the six-country analysis. The United Kingdom has negative net connectedness since 2008. Germany also had negative net connectedness from 2003 through 2010 (with the exception of a brief period in 2008). As we argued above, the persistence in negative net connectedness shows that the dynamics of the German industrial production is driven by other countries.

The directional connectedness measures for Italy is substantially different from the ones obtained in the six-country case. In the 10-country case, Italy has negative connectedness from the end of 2008 until the end of 2010. In the six-country case, on the other hand, it had significant positive net connectedness to others in 2009 and 2010 (see Figure 8.5). The absence of the four BRIC countries, and especially China, from the analysis led to a situation whereby Italy's net connectedness turn up highly positive. In the case of France, the positive net connectedness to others in the six-country case was also observed in the 10-country analysis, but at a smaller scale.

In contrast, starting in early 2011, Italy started to generate connectedness to others that gradually increased throughout 2011. Its net connectedness reached 90% by October 2011. The behavior of the net connectedness is consistent with the slowdown in Italy's industrial production that started in January 2011 and intensified throughout the year. In the case of France, the net connectedness jumped from –70% to 80% in a matter of three months at the end of the sample. French industrial production started to decline in September and October.

The most striking result in Figure 8.8 is the very high level of net connectedness that China attained since the second half of 2008. China's pairwise connectedness to each of the other nine countries increased during this period (see Figure 8.A.7). The 1.7% contraction that the Chinese industrial production suffered in the second half of 2008 led to substantial connectedness to others. As a result, China's net directional connectedness to others increased from 60% in July 2008 to 215% in November 2008. In response to the slowdown in its industrial production and the global recession fears that surfaced after the bankruptcy of Lehman Brothers, in November 2008 the Chinese government announced the plans to implement a $586 billion stimulus package that went into effect immediately in early 2009.[5]

The stimulus package was effective in raising the Chinese industrial production. In the first half of 2009, the industrial production increased by 11.4% and in the second half by 5.7%. The rapid recovery in the Chinese industrial production led to connectedness to other countries. Over the next 12 months, China's net connectedness to others stayed high, fluctuating between 50% and 190%. Given that domestic demand in the United States and the EU member states has stalled since 2009, the robust demand growth in China has become an important source of growth in industrialized countries.[6]

In 2011 the Chinese government and the People's Bank of China worked hard to reign in on inflation. The resulting tight monetary policy led to a slowdown in the growth process again. The growth rate in 2011 declined to less than 9.2%, lower than its longer run growth rate. After fluctuating between –11% and 95% in the first half of 2010, the net connectedness of China jumped to 190% in January 2011 again and stabilized around 120–130% in the second half of 2011.

Finally, the net connectedness indices for Brazil, India, and Russia show that none of the three countries has played a critical role as China since 2008. The net connectedness of all three countries has been negative since 2008. Brazil had some positive connectedness in the mid-2000s while it was growing rapidly. India and Russia, on the other hand, did not have positive net connectedness that lasted longer than a year.

[5] The stimulus package announced by the Chinese government was larger than the combined stimulus packages of Japan and the European Union, but smaller than the amount announced by the U.S. government. In addition, numerous Chinese local governments also announced their own stimulus packages. As a conclusion, it is safe to conclude that the overall Chinese stimulus could be much higher than the official 4 trillion yuan ($586 billion) figure. (See Morrison (2009), p. 6.)

[6] There is widespread consensus among the practitioners about the effectiveness of the Chinese stimulus spending in late 2008 and in 2009: "The last time in late 2008 that economic peril was stalking the United States and Europe, China marshaled the might of its state-directed economy and engineered a muscular rebound that led the subsequent global recovery." (James Kynge, "Cracks in Beijing's Financial Edifice," *Financial Times*, October 9, 2011.)

8.6 CONCLUDING REMARKS

In the final chapter of the book, we have applied the connectedness methodology to the study of business across the leading economies of the world. In doing so, we have also made several important contributions to the literature on international business cycles. To start with, the connectedness index methodology is different from the empirical approaches widely used in the literature. While the factor model approach aims to obtain a world business cycle measure, the connectedness index framework distinguishes between idiosyncratic shocks to industrial production and the connectedness of these shocks across countries. Furthermore, the connectedness index that is based on a multivariate VEC model with one CI equation is better placed to capture the increased co-movement of business fluctuations in more than two countries compared to an analysis based on bivariate correlation coefficients.

Second, the analysis sheds new light on the nature of business cycles, clearly showing that the cross-country co-movement of business fluctuations is not constant over time, nor does it follow an upward trend. Rather, the business cycle connectedness fluctuates substantially over time. However, the band within which the connectedness index fluctuates has increased since 1984. This result is consistent with the findings of both Kose et al. (2003) and Doyle and Faust (2005): When shocks in individual countries are not significant, they cannot be expected to be transmitted to other countries irrespective of the degree of integration among those countries. When the shocks are big enough, the correlation of macroeconomic aggregates across countries will be larger.

Third, the directional connectedness measures are used to identify each country as a gross and/or net transmitter of business cycle shocks to other countries as well as a gross/net recipient of business cycle shocks from other countries over different time periods. The directional connectedness measures show that the United States (1980s and 2000s) and Japan (1970s and 2000s) are the major net transmitters of shocks to other countries, while Germany is the major net receiver of shocks in the 2000s.

Fourth, with an unprecedented jump between May and December 2008, the business cycle connectedness index perfectly captures the global nature of the current recession. Given how fast the business cycles became connected across countries, it is legitimate to argue that the recovery from "the great global recession" requires coordinated policy actions among the major industrial and emerging market economies.

Fifth, we showed that whether a country has a positive or negative net business cycle, connectedness ultimately is closely related to the country's trade balance. Those countries that run trade surpluses tend to be net recipients of shocks, whereas the countries that run trade deficits are likely to be net transmitters of shocks.

Last, but not the least, we added BRIC countries to expand the sample to 10 countries. Qualitatively, the results did not change much. The total connectedness index was significantly higher in the late 1990s and early 2000s than the connectedness index for the G-6 countries. However, the jump in the index in 2008 was not much different from the one we obtained for the G-6 countries. In terms of directional connectedness, China generated substantial net connectedness to others in late 2008 and afterwards. This result supports the view that the Chinese stimulus spending of $586 billion from early 2009 to 2010 helped its domestic industrial production recover and pulled along the other major economies of the world.

8.A APPENDIX: ADDITIONAL TABLES AND FIGURES

Table 8.A.1 Correlation Coefficients—MoM and YoY Growth Rates of Industrial Production (1961:01–2011:12)

	USA	*GER*	*JPN*	*FRA*	*UK*	*ITA*	*CAN*
USA	**1**	0.164	0.202	0.056	0.155	0.132	**0.400**
Germany	0.585	**1**	0.190	0.114	0.149	0.091	0.095
Japan	0.601	0.664	**1**	0.104	0.072	0.057	0.143
France	0.588	0.659	0.642	**1**	0.030	0.051	0.086
UK	0.596	0.527	0.504	0.526	**1**	0.180	0.154
Italy	0.636	0.615	0.693	0.692	0.472	**1**	0.093
Canada	0.872	0.538	0.578	0.576	0.582	0.598	**1**

Notes: Correlation coefficients for the month-on-month (MoM) and year-on-year (YoY) growth rates are reported above and below the diagonal, respectively. As Canada's industrial production data starts on January 1961, the correlation coefficients for the month-on-month (year-on-year) industrial production growth rates are calculated over the period from January 1961 (January 1962) to October 2011.

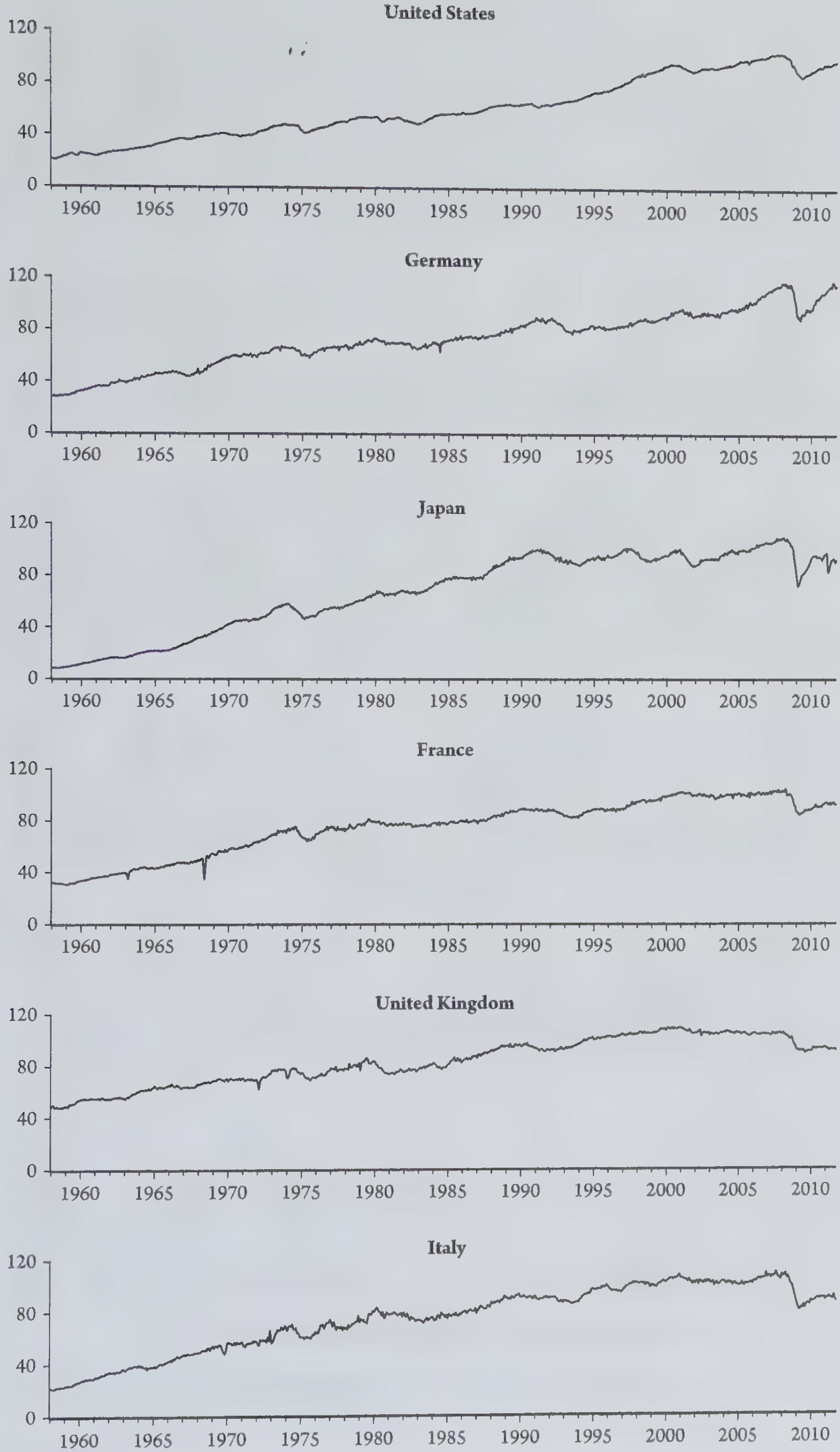


Figure 8.A.1 Seasonally adjusted industrial production indices for G-6 countries (1958:01–2011:12).

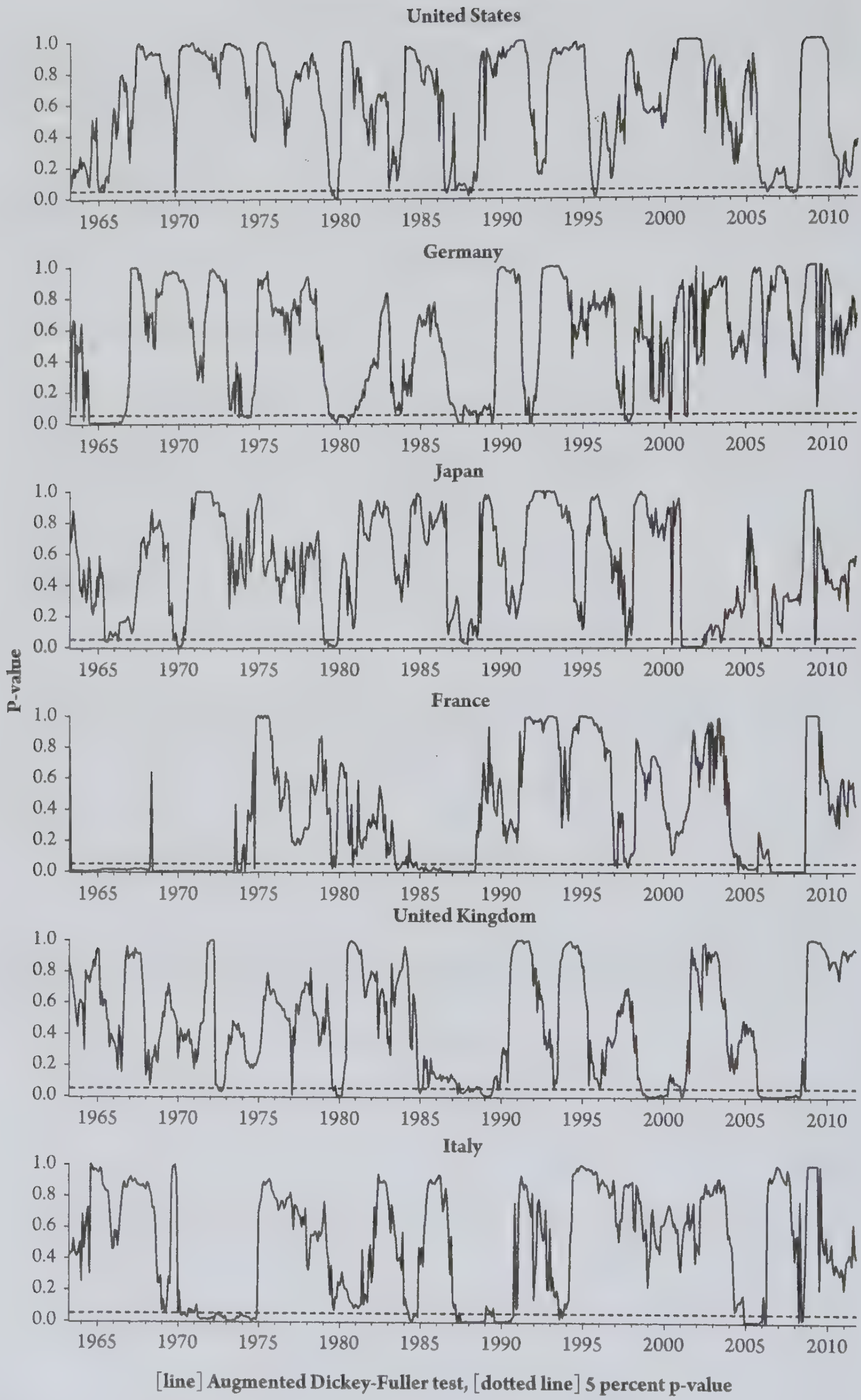


Figure 8.A.2 Augmented Dickey–Fuller test for stationarity in levels.

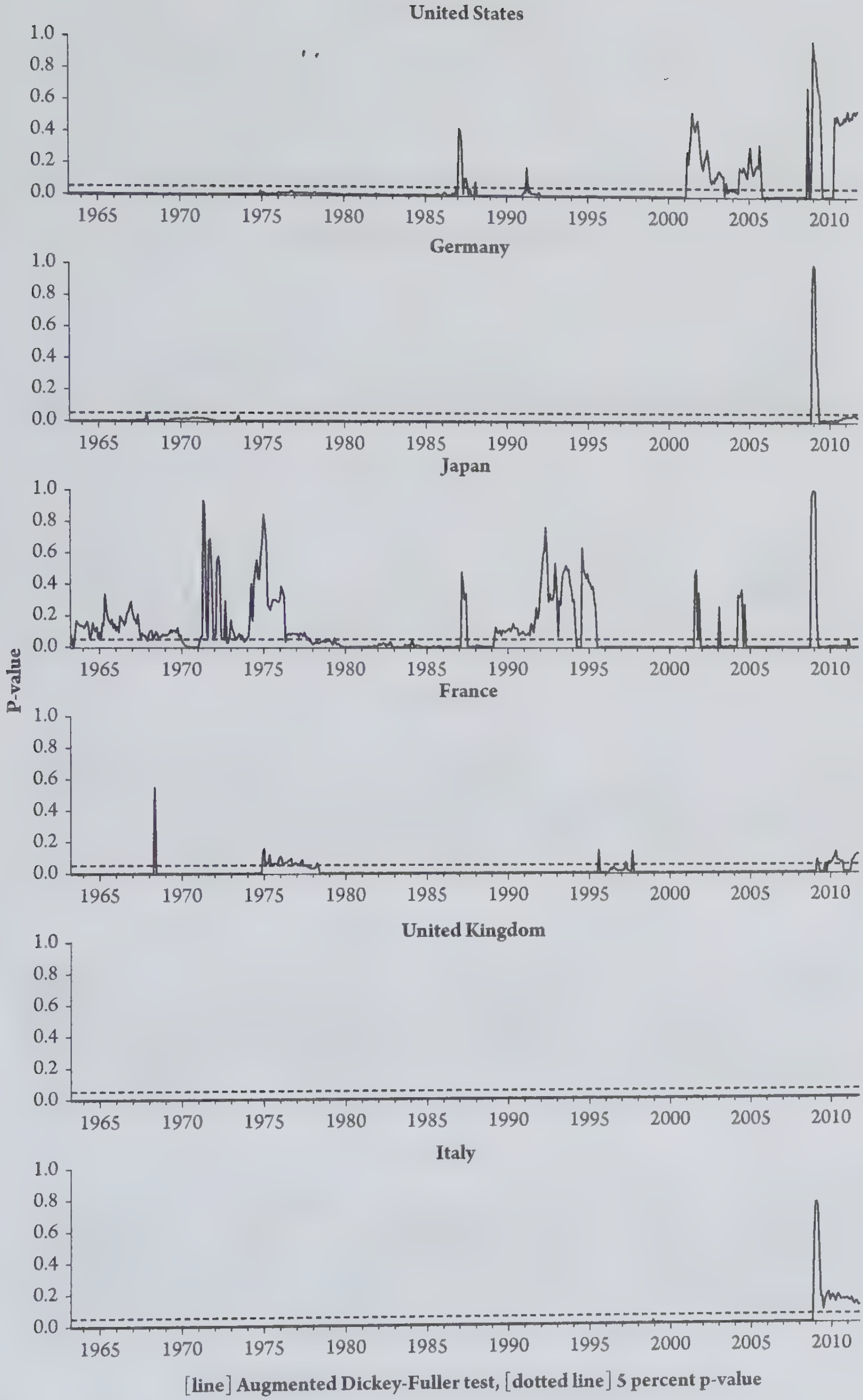


Figure 8.A.3 Augmented Dickey–Fuller test for stationarity in first differences.

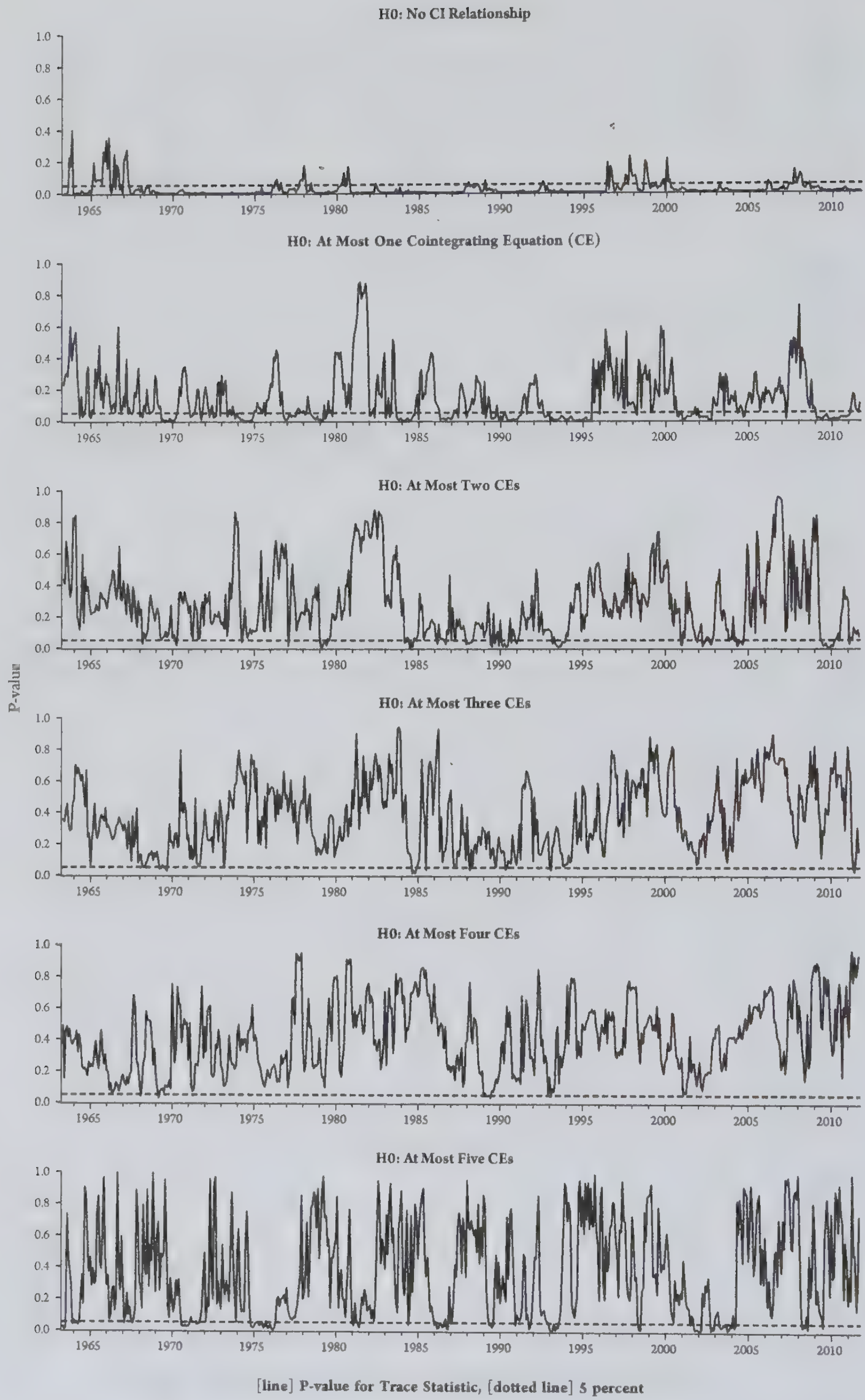


Figure 8.A.4 Johansen co-integration test—trace statistics.

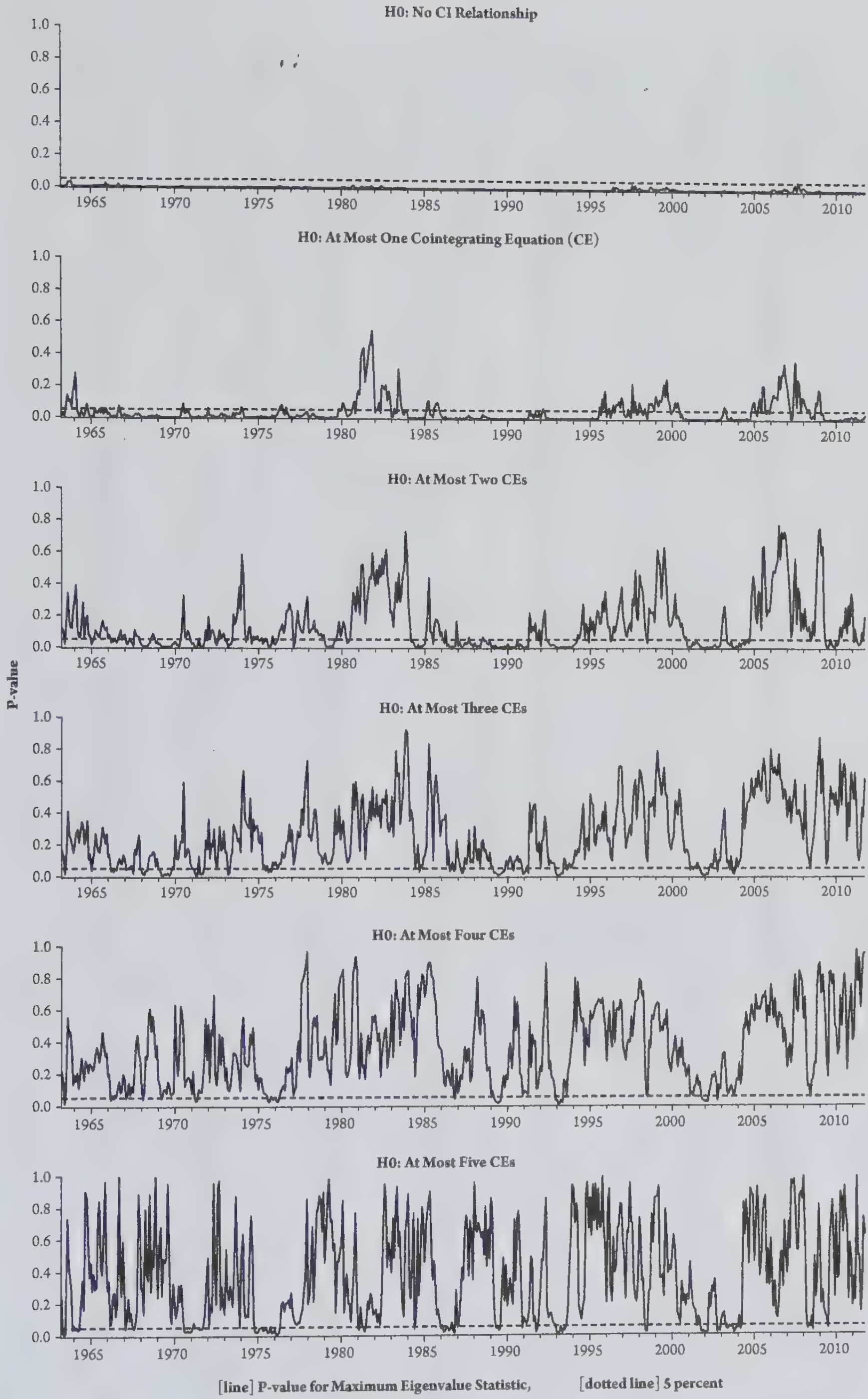


Figure 8.A.5 Johansen co-integration test—maximum eigenvalue statistics.

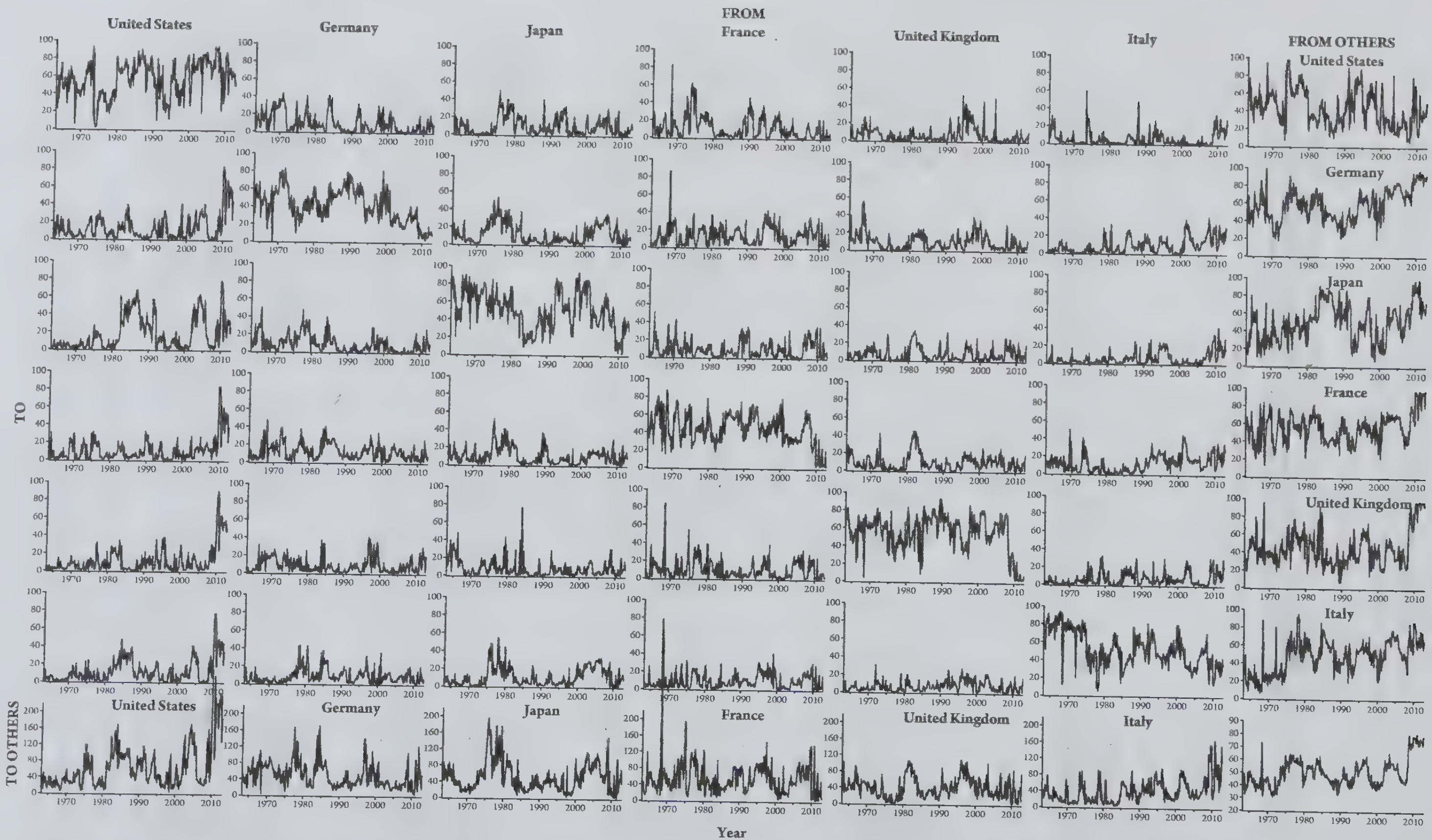


Figure 8.A.6 Pairwise directional connectedness, G-6 countries (1958:01–2011:12).

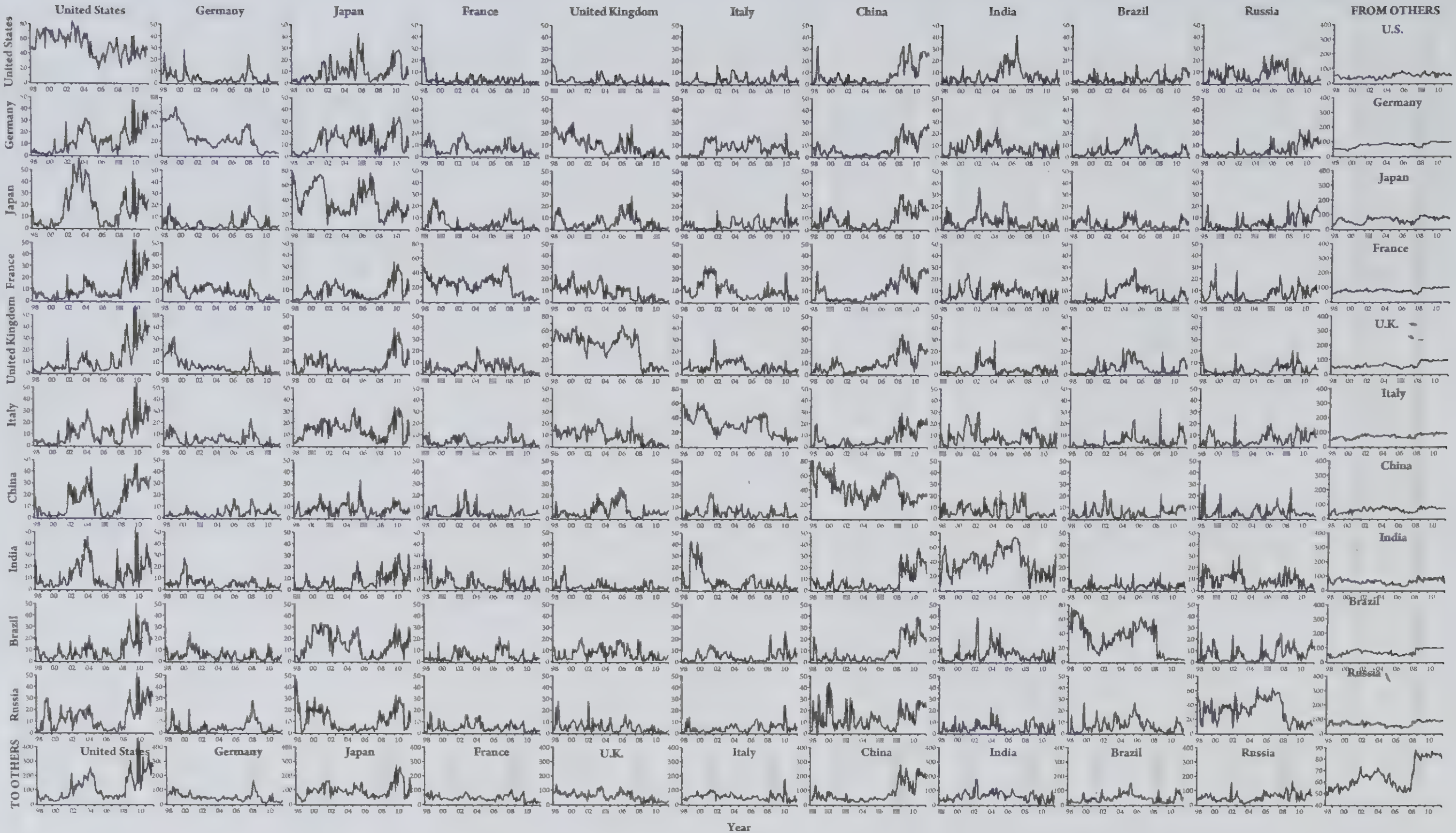


Figure 8.A.7 Pairwise directional connectedness, G-6 and BRIC countries (1993:01–2011:12).

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AUTHOR INDEX

GENERAL INDEX

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FRANCIS X. DIEBOLD is Paul F. and Warren S. Miller Professor of Economics, and Professor of Finance and Statistics, at the University of Pennsylvania and its Wharton School. He is an NBER Faculty Research Associate, as well as an elected Fellow of the Econometric Society, the American Statistical Association, and the International Institute of Forecasters. He has also been the recipient of Sloan, Guggenheim, and Humboldt fellowships and has served as Co-director of the Wharton Financial Institutions Center and President of the Society for Financial Econometrics.

KAMIL YILMAZ is Professor of Economics at Koç University in Istanbul, Turkey, where he has been since 1994. He was previously a visiting professor at the University of Pennsylvania. He holds Ph.D. and M.A. degrees in Economics from the University of Maryland, College Park, and a B.A. degree in Economics from Bogaziçi University in Istanbul. He is the recipient of the 2003 Turkish Academy of Sciences (TÜBA) Encouragement Award for Social Sciences.

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