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Measuring Stock Market Integration of Major Developed and Emerging Economies

As globalization extends its reach across the world, financial markets have become increasingly linked together. Even in the early 1900's, linkages in markets have been evident. The London stock exchange fell two days after the US stock market crash of 1929, a clear sign of existing linkages. With the widespread adoption of new financial technologies and the Internet, investors can access global financial information and buy or sell assets within milliseconds. The rapid advancement of wireless connectivity and proliferation of bilateral trade partnerships the last 30 years has contributed significantly to globalization. As a result, the phenomenon known as financial integration has been rising in economic discussions. It is characterized as a global rise in three key trends: information sharing across financial institutions, cross-country investment and trade, and sharing of financial technologies and methodologies. To measure financial linkages across markets, economists have devised numerous indicators, with varying success. Our study will focus specifically on stock markets. Stock indexes, often thought to be proxy representations of a region's economic activity, are a prime subject for testing levels of integration. Should comovements be detected among international stock markets, one can conclude the existence of linkages. Past studies (e.g. Baumohl and Vyrost, 2010 and Malliaris and Urrutia, 1992) have found one-sided directional correlations and causality between different markets. Since there exist possible time lags in, this heavily implies that some markets "cause" movements in others. Most notable of those are the distinctions between developed and emerging economies. Whether this integration is beneficial to economies is still under heavy debate. Since this phenomenon is recent, there is no widely accepted theory on the effects of financial integration on different economies.

The purpose of this piece is to discuss the existence of financial integration and its effects on developed and emerging markets. In addition, we wish to determine the existence of comovements between different indices through empirical analyses. Finding predictive causality between stock markets provide valuable insight on the levels of financial integration apparent in the international economy and serve as indicators in observing how a financial shock in one market may affect others.

In the first section, we will provide the different theories on the globalization of finance and its macroeconomic effects on international markets. Section II discusses markets of interest and their respective macroeconomic indicators to find suitable markets of interest to be used on the empirical tests. In section III, we discuss the theory and application of the econometric methods to be used in the empirical analyses and provide an overview of data and modifications to our models due to time zone discrepancies. In the fourth and final section, we will present the result of our analysis and make concluding remarks about the implications of our test.

SECTION I.

What is Financial Integration?

Financial integration is defined as the linkages between international financial markets. Broadly, it is the spread of financial information sharing and liberalization of markets in the international stage. Events that occur in an integrated market would trigger responses in foreign markets that are also integrated. This can refer to the flow of money across countries. Since the 1980's, accelerated improvement in financial technology and computing systems coupled with liberalization of international financial and trade laws promoted rapid increases in trade and foreign investment. Countries which were leaning on the capitalist wing during the Cold War,

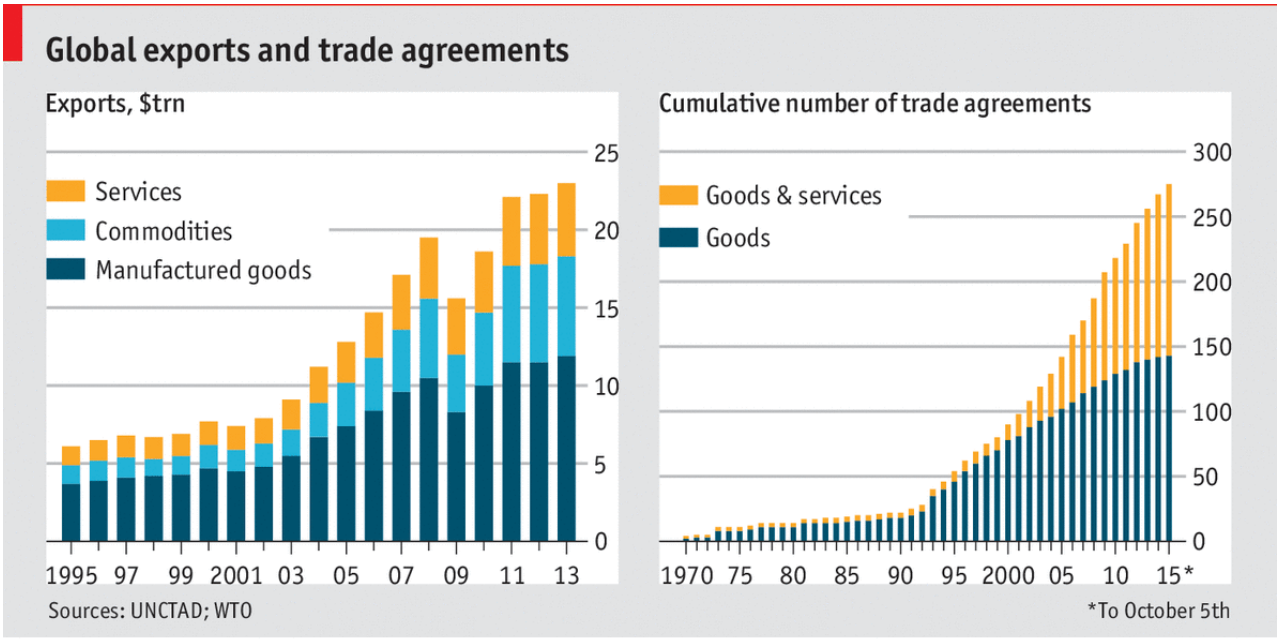
many of which already had advanced economies and held strong political relationships, were among the first to loosen monetary barriers. The world economy was moving towards globalization and stronger integration.

There are multiple measures of financial integration. These measures are generally split into two categories: political and economic. Kose et al. (2009) note that political measures take three forms. These policy-minded indicators are categorized under *de jure* integration. The first political gauge is a government's control on exports and imports, in the form of export controls and tariffs respectively. A second political measure is quantity and price controls. Kose also argues that these economic controls cannot be used independently to measure integration, citing China's lack of control on extensive capital outflows in recent years despite already stringent regulations on foreign reserves.[1] The third indicator are international trade treaties. Recent increases in trade agreements signify a growing shift in many nations' GDP from domestic production to exports. At higher levels of trade to GDP ratios, a country's economy is more susceptible to exogenous shocks in the global economy. A boost in trade deals also signify movement towards economic openness. These political measures cannot be used to independently verify the strength of actual integration, as economic actors may not pursue foreign opportunities despite the lack of government restrictions for reasons such as economic instability and lack of accurate information.

De facto forms, or the economic measures are said to be better indicators of integration, since they display information on actual economic activity rather than political. The two main economic measures of integration are trade levels and comovements among asset prices. In the past two decades, there has been a dramatic increase in trade from an average of $7 trillion

[1] Balding, Christopher. "Why China Can't Stop Capital Outflows" https://www.bloomberg.com/view/articles/2016-12-06/why-china-can-t-stop-capital-outflows

annually in the 1990's to nearly $23 million in 2015. This falls in line with the number of international and regional trade agreements, which saw a spike in the 1990's and continuing today. Note that trade deals are considered de jure integration indicators. The following figure provided by The Economist is shown below[2]



The gross stocks of foreign assets and liabilities to GDP ratio has been used by multiple economists (Kose et al. 2009, Lane and Milesi-Ferretti 2003, Bloomstrom and Kokko 2003) a likely indicator of financial integration. China's lack of control on foreign asset outflows despite policy attempts signify its actual level of integration with global markets: quite high.

The second measure of integration within financial markets are the existence of comovements among international markets. In markets that are financially integrated, prices and capital should be continuously moving to spread and equalize risk. Stock markets are particularly

[2] Infographic provided by The Economist at http://www.economist.com/blogs/graphicdetail/2015/10/global-trade-graphics

affected by capital controls. Korajczyk (1996) argues that the price differences between unrestricted vs restricted equity shares with identical payoffs are direct indicators on the degree of capital controls. In their empirical analysis, they find stronger evidence for integration among developed markets, while emerging markets have lower overall integration. That said, they show evidence of integration among emerging markets increasing over time as the trend of liberalization continues. Foreign currencies are also noted to exhibit comovements between integrated markets.

Stock Market Integration

Stock markets that are heavily integrated are said to price both global and local risk factors. In an integrated environment, rational investors look to events and risks abroad which may alter their domestic markets. Since markets are long considered to be a proxy for economic wellbeing, there is reason to suspect that economic integration would lead to stock market integration. The case for the efficiency hypothesis, in which markets are theorized to be priced according to all information available, is strengthened. Advocates of this theory argue financial liberalization exposes markets to additional global information and consider the effects of cross-country economic relationships in their behavior. In the search of fundamental indicators of stock market integration, economists have recently been focusing on several measures. The most commonly tested are economic growth, foreign investment, market liquidity, trade flow, financial openness, and geographic proximity. According to Chinn and Forbes (2004), despite increases in financial openness in the 1990s, foreign investment and economic growth remain weak indicators of integration while bilateral trade levels are the strongest for determining the magnitude of cross-country linkages. Hence, countries that have higher absolute trade levels are

shown to be more integrated. What the authors do not consider are government controls and economic stability, both of which can be significant measures of foreign investment in a stock market.

Limits on foreign investors and economic stability are often included in discussions of stock market integration. Levine and Zervos (1998) conclude that as market controls are loosened, emerging markets become more internationally integrated and liquid. This takes the form of comovements and volatility in their markets. The availability of public information is often overlooked but another large factor in market integration. A dearth of financial information in a country is likely to deter potential foreign investors in buying into that market, no matter how available domestic shares are for purchase. This goes hand-in-hand with investor perceptions of market stability. While China lacks control over its currency flight, it effectively segments its own stock market simply through implementing laws which prohibit foreign buyers. For example, in the stock exchanges within China, authorities distinguish stocks by labeling shares under "A", "B", and "H" categories. "A" shares are priced in the renminbi currency and is restricted to domestic investors and "B" and "H" shares are priced in US dollars and available to foreign and domestic investors. The number of "A" shares in the exchange vastly outnumber "B" and "H" shares with market capitalizations of around US$4,683 billion to US$1,356 billion for the two segments[3]. Hence, the Chinese market is said to be less liberalized, although steps such as the Hong Kong-Shanghai and Hong Kong-Shenzhen partnership programs are being taken to encourage foreign investors. On the other hand, markets such as the US and Japan allow foreign investors to buy any share with only the addition of regulatory hurdles. Hence, we can expect that Chinese investors may be involved in the US and Japanese stock markets, but the opposite to

[3] Source: Matthews International Capital Management (2015) China's Equity Market Universe

be untrue. Multiple emerging countries have their own protectionist restrictions to protect their vulnerable economies from external shocks.

However, even with open-door policies that allow foreign purchases of domestic shares, foreign investors may not choose to enter certain markets and increase integration. This is mainly due to lack of quality information on firms and domestic markets. Levine and Zervos point out in the same piece that information availability, international accounting standards, and investor protection laws play a key role in determining the entry of foreign investors. Especially endemic to emerging markets, the simultaneous existence of these three requirements are usually variable. For example, Jordan has little restriction on foreign investment but rarely publishes share information and has poor accounting standards. India has an extremely large market size and is accelerating financial market development, yet faces the challenge of corruption[4]. If investors do not feel confident their assets will be protected adequately, they will not engage in a stock market regardless of political and economic openness.

SECTION II.

Markets of Interest

For this piece, we will be measuring integration between large developed and emerging markets. Five markets, three developed and two emerging, will be selected to provide enough subjects without over-complicating the analysis. The markets of interest are the US, Japan, and the UK. These three markets are known for their innovation-driven economy, loose controls on their stock markets, strong investor protection laws, and public financial information. Along with being among the largest economies, they share large trade flows. From their harmonious military

[4] Schwab, Klaus and Sala-i-Martin, Xavier. The Global Competitiveness Report 2016-2017. *World Economic Forum*.

and economic alliances, investors would view their risk of conflict to be low or at least not prone to unexpected shocks. Price levels as measured by inflation and interest rates, sound economic indicators of consumption and investment according to Chee-Wooi and Kim-Leng (2007), have not experienced much volatility. This would maintain investor confidence in the stability of their capital and trade relations. Hence, one can hypothesize that the three developed markets would be less volatile and heavily integrated at bidirectional levels.

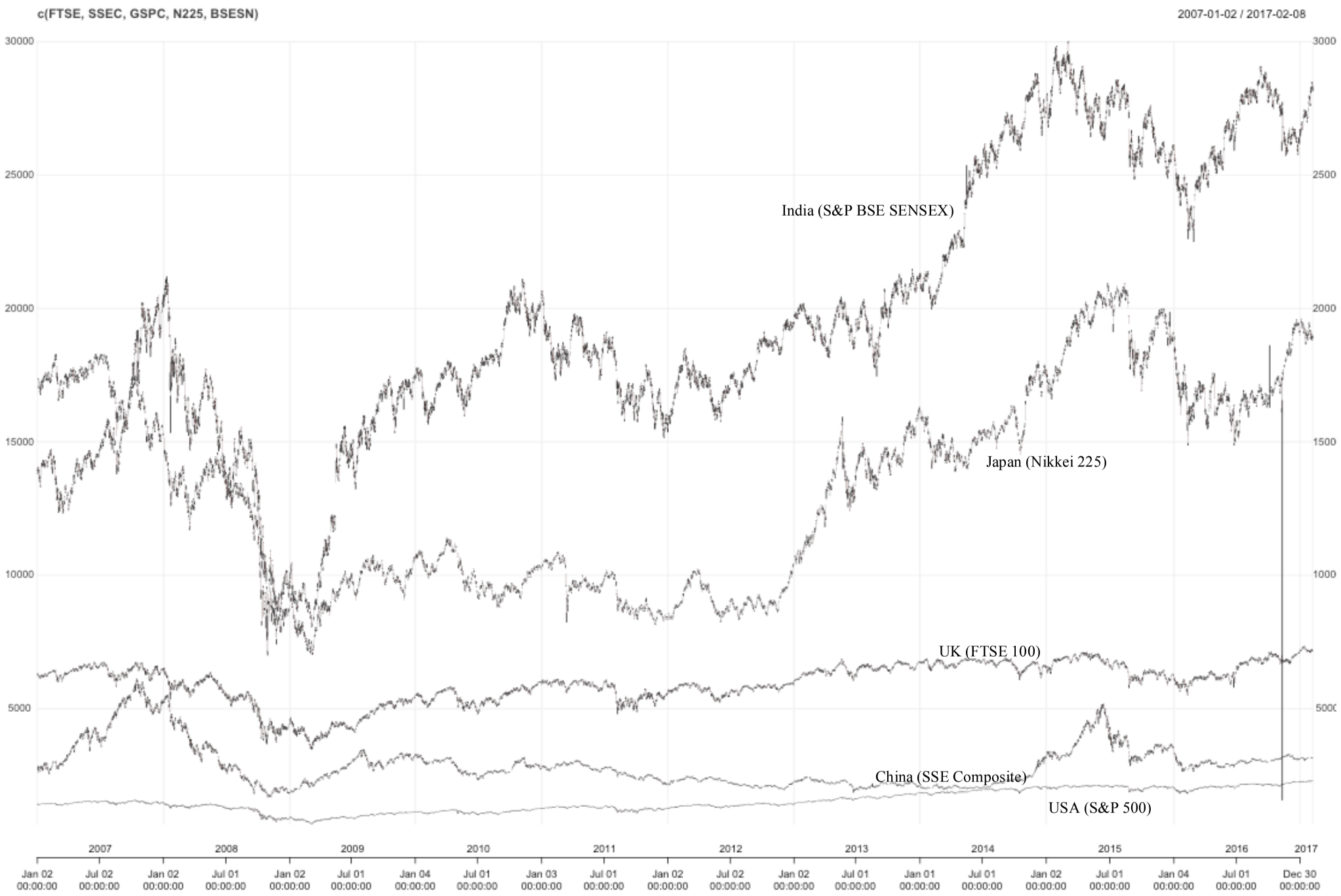
In selecting the major developing markets, we selected the two with the largest market capitalization: China and India. Dubbed the "up-and-coming" economies, these two nations have the largest populations and in recent times have been experiencing high growth rates. This has, of course, not been true for China. Its economy has begun to slow down, posting the lowest growth rates since 1990 during the fiscal year of 2016[5]. Nonetheless, these export-oriented countries are two large manufacturing and service hubs. Their trade flows with each other and the three developed nations mentioned above are extensive. China remains India's largest import destination of goods.[7] However, India only represents 0.91% of imports into China.[7] China and India were the first and ninth largest goods trading partners with the US in 2015.[6] With respect to Japan, China holds the position of the largest trade partner, with the US being a close second, for 2014.[7] For the UK, China and India held first and second respectively for number of goods imported.[7] Considering the rankings of exports, we can expect China to be more heavily integrated than India.

[5] Gough, Neil (2016) China's Fading Factories Weigh on an Already Slowing Economy. *New York Times* https://www.nytimes.com/2016/01/20/business/international/china-economy-slowdown.html

[6] Office of the United States Trade Representative

[7] The Observatory of Economic Complexity (MIT) http://atlas.media.mit.edu/en/profile/country/jpn/

To represent each market, the domestic stock index with the largest market capitalization are selected. Thus, the indices selected are S&P 500 for the US, FTSE 100 for the UK, Nikkei 225 for Japan, SSE Composite for China, and BSE SENSEX for India. Note that while we are testing indices, we will refer to them using their respective country names in our analyses. Their ten-year prices are shown below:


c(FTSE, SSEC, GSPC, N225, BSESN)
2007-01-02 / 2017-02-08
India (S&P BSE SENSEX)
Japan (Nikkei 225)
UK (FTSE 100)
China (SSE Composite)
USA (S&P 500)
30000
25000
20000
15000
10000
5000
3000
2500
2000
1500
1000
5000
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
Jan 02 00:00:00
Jul 02 00:00:00
Jan 02 00:00:00
Jul 01 00:00:00
Jan 02 00:00:00
Jul 01 00:00:00
Jan 04 00:00:00
Jul 01 00:00:00
Jan 03 00:00:00
Jul 01 00:00:00
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Jan 01 00:00:00
Jul 01 00:00:00
Jan 02 00:00:00
Jul 01 00:00:00
Jan 04 00:00:00
Jul 01 00:00:00
Dec 30 00:00:00

SECTION III.

Empirical Approaches on Measuring Stock Market Integration

Due to its recent nature, the scope on the study of integration specifically within stock markets have been much more observational in nature. There are multiple methods of determining stock market integration. Korajczyk (1996) applies an equilibrium model of stock returns assuming perfect integration and compares it to the actual returns of different national markets. If the behavior of a market exhibits large deviations from the equilibrium model, that market is determined to be less integrated. As mentioned in the previous section, they find that deviations are generally higher in emerging markets and correlates with the level of protectionist controls found in developing nations.

The presence of large price movements can influence reactions in other markets. Due to geographic spreads and differences in market operation times, one market will have additional information from other markets that open sooner. Examining specific firm-level relationships would be unproductive due to the complex characteristics of each firm's risks and returns. Regional indexes are designed to be proxies of firm-level share prices and provide general information on their respective markets. The nature of this relationship make stock indices prime subjects Granger-causality tests, where temporal gaps due to time zones create an opportunity to discover causal or predictive significance.

There are two general applications of Granger-causality tests to analyze market integration: short-term and long-term. Short term analyses consist of segmenting time-series data into multiple periods to uncover changes in causal relationships between markets before, during, or after a date. This form is usually used to study the effects of a specific event, usually a major event such as financial crisis. Malliearis and Urrutia (1992) conduct a segmented test to study the

crash order of the October 1987 crisis. They found that although no leading relationship exists, there was considerable increase in bidirectional causality during the crash. The London market led the Hong Kong market, which led other Asian markets. The Tokyo market led Singapore while following the New York market. The lack of a clear order in causal relationships suggest that the crash happened simultaneously among all markets.

The other form, being long run, is a causality test performed over a continuous long-term time series. Instead of examining specific-event driven segments, this method analyzes relationships of markets over a single period, considering all events and movements within the series. For example, Baumohl and Vyrost (2010) conduct causality tests on markets over a ten-year range from January 2000 to September 2010. They found strong indications of bidirectional causality in almost all five of their indices chosen (S&P 500, FTSE 100, DAX, HSI, N225) at the 0.05 significance level. There were two exceptions. N225 was found to not granger-cause HSI and the FTSE was found to not granger-cause DAX. However, the reverse is true for both relationships. These results of non-bidirectional causality are interesting considering both pair's close geographic and economic ties.

Relevant Econometric Techniques

Among multiple methodologies used to assess stock market integration, we have selected the Granger-causality test for assessing integration. This method is preferred for our purposes over the equilibrium model proposed by Korajczyk due to its ease of calculation, reproducibility, and less reliance on critical assumptions. We will also be applying two additional statistical tests for maintaining the Granger-causality test's assumption of stationarity and the optimal maximum

lag selection: the augmented Dickey-Fuller test (ADF) and Akaike's Information Criterion (AIC) respectively.

1. Granger-Causality

The Granger-causality test, first published by Clive Granger (1969), is applied to a pair of time series and assesses whether one series is useful for forecasting the other. It is emphasized that true causality cannot be implied upon confirmation of the existence of Granger-causality. Hence, the term "Granger-cause" is applied. The test for time series *A* and *B* are conducted by deploying a VAR model in which series *A* is regressed by the autoregressive lags of itself and the autoregressive lags of the series *B*. It is compared a simple AR model of series *A* to assess whether the addition of parameters estimating series *B* contribute predictive power in forecasting series *A*. Assuming we are testing if series *B* Granger-causes series *A*, the VAR and AR models are displayed below

$$A_t = \beta_0 + \sum_{i=1}^{p} \beta_i A_{t-i} + \sum_{j=1}^{p} \gamma_j B_{t-j} + u_t$$

$$A_t = \beta_0 + \sum_{i=1}^{p} \beta_i A_{t-i}$$

where p is the maximum number of lagged observations and u_t are residuals at time t. To determine causality, an F-test comparing the two models is conducted under the null hypothesis that the addition of series *B* in predicting *A* does not improve accuracy. A rejection of the null hypothesis shows that granger-causality is evident. The optimal maximum lag is chosen using various information criterion, of which we will be using the Akaike's information criterion. We will discuss the relevance of the AIC specifically pertaining to VAR models after reviewing stationary processes and the augmented Dickey-Fuller test.

The incorporation of $A_{t-1}+...+A_{t-p}$ as explanatory variables is to include the effects of autoregressive processes. Autoregressive properties refer to the notion that in time series analysis, there can be temporal correlation between a series and its past values. Models that incorporate autoregressive parameters capture this information, which can be used to improve forecast predictions. If the inclusion of parameters $B_{t-1}+...+B_{t-p}$ at as an explanatory variable is shown to improve the prediction of A_t, then series *B* is said to granger-cause series *A*. A second test reversing explanatory and response variables is then conducted. If series A is said to granger-cause series *B*, but series *B* does not granger-cause series *A*, we say that there is unidirectional causality from series *A* to series *B*. If series *A* granger-causes series *B* and the reverse is also true, then there is evidence of bidirectional causality.

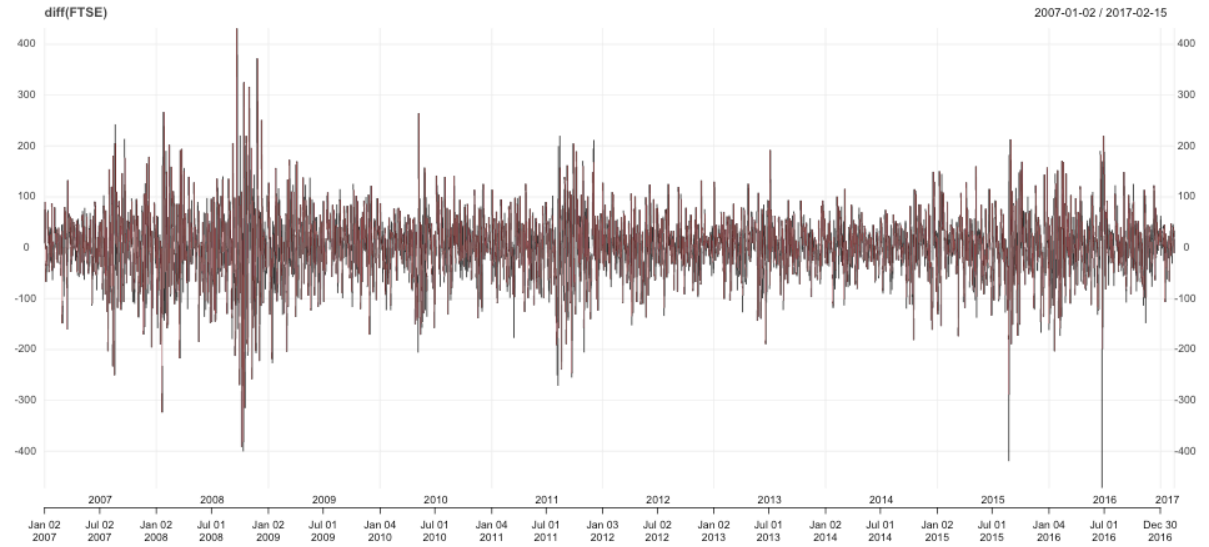
The key assumption of this model, as with most time-series models, are that the time series involved have stationary processes. Next, we will describe the meaning of a "stationary" time-series process, the statistical test to determine the two, and remedies.

2. Stationary Processes and the Augmented Dickey-Fuller (ADF) Test

As mentioned above, the Granger-causality test must be performed on two time-series that both exhibit stationary processes. A stationary process is defined as stochastic process who's mean and variance is roughly constant over time. AR and VAR models both require stationary time-series processes for correct specification. This is due to the statistical attractiveness of independence and homoscedasticity, which are also highly desired in cross-sectional and panel analysis. Most stock indexes are found to be nonstationary due to time trends. For example, below is a chart showing the ten-year raw closing prices of the FTSE 100 index[8].

[8] Plots generated using Yahoo! Finance data streamed using the Quantmod R package.

To the naked eye, the series displayed above appears to be nonstationary. Time-dependent trends are apparent. A quick visual analysis suggests the mean and variance differ over time. If found to be nonstationary, the series is to be differenced until it is stationary. Since differencing takes only changes over values over time rather than absolute values, it stabilizes the mean and variance. The FTSE 100 index appears stationary after differencing once, or $\Delta x_t = x_t - x_{t-1}$, as shown below



The mean now appears to be constant around zero while variance, except for a few notable outliers, is also constant. Since there appears to be outliers, this visual itself is not useful due to the large number of data in the time-series. This is where one must rely on quantitative tests to definitively conclude results.

The Dickey-Fuller test, conceived by as the name suggests Dickey and Fuller (1979), tests whether a time-series is stationary. We will use a modified version called the augmented Dickey-Fuller test, or ADF, to additionally control for autocorrelation. While there are three versions to account for different behaviors, we will use the version that considers the presence of time-dependent trends. The ADF test takes the form

$$\Delta y_t = \beta_1 + \beta_2 t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + u_t$$

where y is the time series value at time *t*, β_1 is the constant, β_2 is the coefficient of the time trend at time *t*, γ is the coefficient focus of the test, *p* is the maximum number of lags of first-difference autoregressive process, and u_t is the error term.

Main attention will be on γ. The null hypothesis is $\gamma = 0$, while the alternate hypothesis is $\gamma < 0$. If the null hypothesis is rejected, the time series is stationary and fit to be modeled. Note that the test has its own modified t-distribution to assess significance. Lag lengths are, like the Granger-causality test, chosen using some information criterion applied on the model. The test assesses for a negative γ since in a stationary process, the series is assumed to oscillate around a constant mean. A negative value would follow a positive value, and vice versa. Hence, the subsequent change should have a negative coefficient from the previous. If found to be

nonstationary, the series will need to be corrected by additional differencing until found to be stationary.

3. Akaike's Information Criterion

Both the Granger-causality test and ADF test requires the selection of a lag length that best fits their respective models. While one may run the models with different lag lengths and accept the lag that bests fit the models, this method of lag selection is vulnerable to overfitting. Statisticians use information criterion to select models which provide insight on the different model specifications while considering the dangers of overfitting. While there are many available, the one we will be using is the Akaike's Information Criterion, or AIC, devised by statistician Akaike (1997). The form is below

$$AIC = 2k - 2ln(L)$$

where L is the maximized likelihood function value of the model and k is the number of parameters estimated. The objective is to select the model with the lowest AIC, which is an absolute number. Note that this information criterion provides a favors smaller residual errors and acts as a buffer against overfitting by penalizing models that increase in parameters used.

Data and the Implications of Time Zones and Holidays

For the analysis, we will use closing prices as they best represent daily returns. They reflect changes throughout the trading day more accurately than opening, high, or low prices. Dates represented are from a roughly ten-year period from January 2nd, 2007 to February 2nd, 2017. Excluding holidays, there are about 1978 closing prices per index. One crucial consideration we must make is on time synchronization. Markets on a given day open first in

Asia, then Europe, then finally the Americas. For example, by February 18th 9:30am Eastern Time, when the US market opens, it is already 10:30pm the following day in China. The Chinese market has already closed. Hence, when testing whether a US index Granger-causes a Chinese index, one must set the Chinese index at the following day or at $t+1$. When testing whether a Chinese index Granger-causes a US index, the same day can be applied or at t since the Chinese market opens earlier. The same logic is applied to testing US and European markets, and European and Asian markets. After accounting for time zones, we simply remove dates where at least one market has a holiday.

We now move onto determining whether the closing price observations are stationary using the ADF test. Upon running the test, we find every series is nonstationary and requires first-order differencing to maintain stationary processes. After a second ADF test on the differenced series, we can conclude that every differenced index is stationary. This analysis will essentially be applied to daily changes in closing price. Using the lowest AIC for each pair to find optimal lag lengths, we may now conduct the Granger-causality test.

SECTION IV.

Results

The result of our analysis is shown below

Response		Explanatory	Lead Effect (t+1)	Lag length	F-statistic	P-value
USA	←	India	FALSE	5	2.553256	0.02601439*
UK	←	India	FALSE	3	1.181957	0.3151698
China	←	India	TRUE	1	0.2871922	0.5920892
Japan	←	India	TRUE	1	0.007810758	0.9295853
Japan	←	UK	TRUE	7	3.477895	0.001042492*
India	←	UK	TRUE	3	2.579998	0.05202611
China	←	UK	TRUE	5	1.343865	0.2429054
USA	←	UK	FALSE	6	1.166647	0.3213799
UK	←	USA	TRUE	6	2.664228	0.01411232*
Japan	←	USA	TRUE	4	2.477773	0.04231998*
China	←	USA	TRUE	1	0.9363915	0.3333327
India	←	USA	TRUE	1	0.07903679	0.7786381
UK	←	Japan	FALSE	5	2.03726	0.07064744
India	←	Japan	FALSE	1	0.3089545	0.5783889
USA	←	Japan	FALSE	4	1.524743	0.192362
China	←	Japan	FALSE	1	0.02328872	0.8787251
UK	←	China	FALSE	4	3.39845	0.008872218*
USA	←	China	FALSE	3	3.059369	0.02726155*
India	←	China	FALSE	1	1.676797	0.1955103
Japan	←	China	FALSE	1	0.09889975	0.753189

* Indicates significance at 5% level ($P < 0.05$).

Contrary to our expectations, there is no wide range of bidirectional causality between the indices of developed nations. The UK appears to unidirectionally Granger-cause Japan, while Japan does not seem to influence any of the four other markets. Unsurprisingly, the USA unidirectionally Granger-causes the two other developed markets. Our hypothesis is partially correct in that neither indices of emerging markets would be Granger-caused by the developing

nations, but they influence developed markets. For example, the China influences British and American markets. Interestingly, despite extensive trade relations, China does not appear to Granger-cause Japan. Meanwhile, India displays statistical significance in Granger-causing the UK. Another potential issue is the presence of holidays, while we resorted to removing dates which contain a holiday, this may cause discrepancies since differencing requires daily changes in prices.

Conclusion

The continued use of capital controls on stock markets effectively insulates China and India from international integration. Especially for developing markets, capital controls are still the de facto method of protecting the economy from outside shocks, while allowing their domestic investors to invest internationally. We see that developed nations with open markets have mixed but considerable integration, with the key leader being the US market. In a post-crisis world economy, the continued influence of the US economy on other markets reveal risks to developed economies. Should another market crash occur, we will surely witness additional comovements in advanced economies. Other comovements linking smaller developed economies would contribute to additional damages. Since this phenomenon has only been studied starting in the 1980's, there has been no definitive theories on investor choices at a microeconomic level. Additional research on more determinants and the long-term effects of market linkages on the international scene is needed.

R Script available @ https://github.com/clam140/measuring-stock-market-integration/

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