Intermediary Asset Pricing: New Evidence from Many Asset Classes

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Abstract

We find that shocks to the equity capital ratio of financial intermediaries—*Primary Dealer* counterparties of the New York Federal Reserve—possess significant explanatory power for cross-sectional variation in expected returns. This is true not only for commonly studied equity and government bond market portfolios, but also for other more sophisticated asset classes such as corporate and sovereign bonds, derivatives, commodities, and currencies. Our intermediary capital risk factor is strongly pro-cyclical, implying counter-cyclical intermediary leverage. The price of risk for intermediary capital shocks is consistently positive and of similar magnitude when estimated separately for individual asset classes, suggesting that financial intermediaries are marginal investors in many markets and hence key to understanding asset prices.

Keywords: Sophisticated asset classes, primary dealers, intermediary capital, leverage cycles

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1 Introduction

Intermediary asset pricing theories offer a new perspective for understanding risk premia. These theories are predicated on the fact that financial intermediaries are in the advantageous position of trading almost all asset classes, anytime and everywhere. For instance, Siriwardane (2015) shows that in 2011 about 50% of total net credit derivative swap protection in the U.S. was sold by the top five dealers.[1] In the corporate bond market, more than 95% of bonds are traded in over-the-counter markets, in which dealers are necessarily involved.[2] It is likely that intermediaries are marginal investors in many asset markets, and that their marginal value of wealth is a plausible pricing kernel for a broad cross-section of securities.

This view stands in contrast to standard consumption-based models in which the focal pricing kernel is that of the household (e.g., Campbell and Cochrane (1999); Bansal and Yaron (2004)). Households' comparative lack of expertise in trading assets, especially sophisticated ones like derivatives or commodities, casts doubt on the viability of household marginal utility as a unified model for jointly pricing the wide array of traded assets in the economy.[3] Our hypothesis, inspired by intermediary asset pricing theory, is that the classic risk-return asset pricing trade-off is more likely to hold once we replace the first-order condition of unsophisticated households with that of sophisticated intermediaries.

The central challenges facing this hypothesis are (i) how to identify a set of financial intermediaries that are marginal investors in many markets, and (ii) how to measure their marginal utility of wealth in order to construct the pricing kernel. For the first choice, we focus on *primary dealers* who serve as counterparties of the Federal Reserve Bank of New York ("NY Fed" henceforth) in its implementation of monetary policy. Primary dealers are large and sophisticated financial institutions that operate in virtually the entire universe of capital markets, and include the likes of Goldman Sachs, JP Morgan, and Deutsche Bank.[4]

[1] All dealers as a whole are responsible for 80% of the net CDS sales in 2011. On the buy side, all dealers comprise 55% of net CDS purchases, and the top five dealers account for 25% of CDS purchases.

[2] These trades are reported in the Trade Reporting and Compliance Engine (TRACE) database. According to Edwards, Harris, and Piwowar (2007), fewer than 5% of bonds are listed on the NYSE, and trades occuring via NYSE's Automated Bond System (ABS) are almost all from small retail investors. In contrast, only 2% of corporate bond trades in TRACE are from retail investors.

[3] Vissing-Jorgensen (2002) and Calvet, Campbell, and Sodini (2007) document limited stock market participation by households.

[4] Primary dealers as of 2014 are listed in Table 1, and the list of all primary dealers since 1960 is in Table A.1.

Our second choice is guided by the recent intermediary asset pricing models of He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014). In these models, following the tradition of Bernanke and Gertler (1989) and Holmstrom and Tirole (1997), the intermediary sector's net worth (or, equivalently, its equity capital ratio) is the key determinant of its marginal value of wealth. When the intermediary experiences a negative shock to its equity capital, say due to an unexpected drop in the securitized mortgage market, its risk bearing capacity is impaired and its utility from an extra dollar of equity capital rises.

Prompted by these theories, in Section 2 we propose a model for the intermediary pricing kernel that is composed of two-factors: the excess return on aggregate wealth, and the shock to intermediaries' (equity) capital ratio. The return on aggregate wealth captures the usual Total-Factor-Productivity-style persistent technology shock that drives general economic growth. Innovations to the intermediary capital ratio capture financial shocks that affect the soundness of the financial intermediary sector, arising for example from shocks to agency/contracting frictions, changes in regulation, or large abnormal gains/losses in parts of an intermediary's portfolio. We show how this pricing kernel arises in the theoretical framework of He and Krishnamurthy (2012).

We construct the aggregate capital ratio for the intermediary sector by matching the New York Fed's primary dealer list with CRSP/Compustat and Datastream data on their publicly traded holding companies (see Section 3). We define the *intermediary capital ratio*, denoted η_t, as the aggregate value of market equity divided by aggregate market equity plus aggregate book debt of primary dealers active in quarter t:

$$\eta_t = \frac{\sum_i \text{Market Equity}_{i,t}}{\sum_i \left(\text{Market Equity}_{i,t} + \text{Book Debt}_{i,t}\right)}.$$

Our main empirical result is that assets' exposure to intermediary capital ratio shocks (innovations in η_t) possess a strong and consistent ability to explain cross-sectional differences in average returns for assets in seven different markets, including equities, US government and corporate bonds, foreign sovereign bonds, options, credit default swaps (CDS), commodities, and foreign exchange (FX).

We perform cross-sectional asset pricing tests both independently within each asset class, as well as jointly using all asset classes. By comparing the risk price on intermediary capital shocks estimated from different sets of test assets, we can evaluate the model assumptions that (i) intermediaries are marginal pricers in all markets and (ii) their equity capital ratio is a sensible proxy for their marginal value of wealth. In particular, if we find insignificant intermediary capital risk prices for some asset classes, or there exist large disparities in risk prices across markets, then it suggests that (i) and/or (ii) are violated.

To the contrary, we estimate significantly positive prices of risk on the intermediary capital factor in all asset classes, and find that all estimates have similar magnitudes, consistent with the view that primary dealers are marginal investors in all of these markets. Furthermore, we show in placebo tests that equity capital ratios of other sectors do *not* exhibit this property. When we replace primary dealers with non-primary dealers (who tend to be smaller, standalone broker-dealers with little activity in derivatives markets) or non-financial firms, we find large discrepancies in risk prices estimated from different asset classes that are largely insignificant and often have conflicting signs.

Our estimates for the price of risk on intermediary capital shocks carry two important economic implications. First, positivity of the estimated risk price means assets that pay more in states of the world with a low intermediary capital ratio (that is, assets with low betas on η_t shocks) also have lower expected returns in equilibrium. This implies that low capital-risk-beta assets are viewed as valuable hedges by marginal investors or, in other words, that primary dealers have high marginal value of wealth when their capital ratio is low. This conclusion accords with ample empirical evidence that institutional investors become distressed and place higher marginal value on a dollar when their capital is impaired.[5] Our risk price estimates also suggest that intermediary (primary dealer) equity capital ratios are pro-cyclical, or equivalently, that intermediary leverage is counter-cyclical.

The second economic implication arises from the similarity in magnitudes of capital ratio risk prices estimated from different asset classes. As we explain in Section 3.2, in the standard empirical asset pricing framework where one single pricing kernel applies to all assets, the estimated price of capital ratio risk should be the same in all asset classes. We are not that far from this theoretical prediction. The risk price estimated jointly from all asset classes is 9% per quarter. For risk prices

[5] Examples include Froot and O'Connell (1999), Gabaix, Krishnamurthy, and Vigneron (2007), Mitchell, Pederson, and Pulvino (2007), Mitchell and Pulvino (2009), and Siriwardane (2015), among others.

that are estimated independently from each asset class, we find that five of the seven estimates are between 7% and 11%; the estimated risk prices are 22% and 19% for options and FX portfolios, respectively. While we reject the null of 0% in all seven markets,[6] we cannot reject the null of 9% in any individual market. One might expect that trading in different asset classes involves substantially different knowledge, expertise, and terminology; yet all of these markets produce estimated prices of intermediary capital risk with similar magnitude.

This interesting result is broadly consistent with the assumption of homogeneity among intermediaries, which is implicit in essentially all state-of-the-art intermediary asset pricing models. It turns out that this simple "representative intermediary" model goes a long way in explaining the data. Recall that our pricing kernel is a single aggregate capital ratio (as opposed to heterogeneous ratios among intermediaries), and we implicitly assume that this set of intermediaries is marginal in all classes. If instead intermediaries who specialize in specific asset classes have heterogeneous pricing kernels—a reasonable description of the world—then the risk prices identified in different markets may differ. Indeed, we view this as a plausible explanation for the small discrepancy of risk prices that we estimate from different markets. We emphasize that without detailed data on the relative specialization of individual intermediaries, our empirical approach is not designed to test this hypothesis. Our tests cannot differentiate between the same intermediaries being marginal in all asset classes, versus different intermediaries being marginal in each asset class but all having highly correlated capital ratios (and hence the discrepancy of estimated risk prices is small).

An important precursor to our paper is Adrian, Etula, and Muir (2014a) (henceforth AEM), which is the first paper to unite the intermediary-based paradigm with mainstream empirical asset pricing. Our positive price for exposure to primary dealer *capital ratio* shocks contrasts with AEM, who estimate a positive price for broker-dealer *leverage* shocks. These two results are contradictory because leverage, defined as assets over equity, is just the reciprocal of the equity capital ratio. That is, AEM find pro-cyclical broker-dealer leverage while our paper suggests that the leverage of primary dealers is counter-cyclical.

One key piece of evidence supports our choice of proxy for the intermediary pricing kernel compared to AEM. The results of AEM are based on test portfolios comprised of stocks and

[6]For foreign sovereign bonds, we find a t-statistic of 1.66 on the intermediary capital factor, which is significant at the 10% level. In all other markets, the estimate is significant at the 5% level or better.

government bonds. We confirm their main findings that the AEM leverage factor is especially powerful for describing the cross section of stock and bond returns. But when we perform our test pooling all seven asset classes and replace our variable with the AEM factor, the implied price of AEM leverage risk becomes insignificant. When estimated independently by asset class, the AEM risk price changes sign for options, CDS, and FX markets, and for CDS the opposite-sign estimate is statistically significant. This empirical finding is particularly interesting because most intermediary-based asset pricing models are founded on the limits-to-arbitrage paradigm (Shleifer and Vishny, 1997), in which sophisticated financial intermediaries play a central and dominant role in some asset classes (e.g., derivatives contracts or OTC markets) that are too sophisticated for most household investors. In fact, as we acknowledge below, equity is the asset class where we least expect good performance by the pricing kernel of primary dealers.

In Section 4, we explore potential explanations for conflicting results in our analysis versus AEM. Our papers differ in the definition of financial intermediaries and in data sources. AEM focus on the security broker-dealer sector and associated book leverage ratios provided in the Federal Reserve's Flow of Funds. We instead use NY Fed primary dealers and data on their holding companies from CRSP/Compustat and Datastream to construct the market equity capital ratio. We show that the accounting treatment of book versus market values cannot explain these differences, because book leverage and market leverage exhibit a strong positive correlation in our primary dealer sample.

Rather, we argue that the discrepancy in our findings is most likely due to compositional differences in our data. Flow of Funds data only contains information about standalone US broker-dealers and broker-dealer subsidiaries of conglomerates. Our equity capital ratio instead relies on data at the holding company level. The distinction between these two approaches rests on the role of internal capital markets within financial holding companies.[7] Consider, for example, our treatment of JP Morgan Securities LLC, which is one of the largest broker-dealers in the world and a wholly-owned subsidiary of JP Morgan Chase & Co. Flow of Funds data would only reflect the financial health of the subsidiary. If the subsidiary suffers a large trading loss relative to the size of the subsidiary, it will be reflected as broker-dealer financial distress in the Flow of Funds.

[7] Alternatively, balance sheet adjustment across these two intermediary segments could occur via external capital markets (He, Khang, and Krishnamurthy (2010) and Hanson, Shleifer, Stein, and Vishny (2015)). Though beyond the scope of this paper, it is worth exploring the difference between external and internal capital markets in an economy with heterogeneous financial intermediaries.

However, if other businesses of the JP Morgan holding company are thriving, financial distress in the broker-dealer subsidiary may be largely mitigated thanks to its access to internal capital markets. On the other hand, a sufficiently bad shock in one of the holding company's non-dealer businesses (for example in its large mortgage lending activities) can potentially drive the holding company into distress. If losses are severe enough to impair internal capital flow, it will reduce risk bearing capacity in the broker-dealer arm even though the shock originated elsewhere and the dealer's balance-sheet does not reflect ill health. In short, if internal capital markets are important sources of funds for broker-dealer subsidiaries, then financial soundness of the holding company may be a superior proxy for the intermediary sector pricing kernel.[8]

Section 5 provides additional results and a battery of robustness tests. In single factor models without the market factor, our intermediary capital ratio continues to demonstrate large explanatory power for differences in average returns within sophisticated asset classes. We show that our results are qualitatively similar in the pre-crisis sample period 1970Q1-2006Q4, in the more recent 1990Q1-2012Q4 sample period, and when we conduct our tests at the monthly rather than quarterly frequency. Lastly, we report time series evidence that the intermediary capital ratio predicts future returns in five of the seven asset classes we study.

Related Literature

Until recently, the role of financial institutions in determining equilibrium asset prices has been under-appreciated by the finance literature (early contributions include Shleifer and Vishny, 1992, 1997; Allen, 2001). Our paper belongs to a burgeoning literature on intermediary asset pricing, which highlights the pricing kernel of financial intermediaries, rather than that of households, in explaining the pricing behavior of sophisticated financial assets (He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014)).[9] Kondor and Vayanos (2015) study equilibrium asset pricing with multiple assets when arbitrage capital is scarce, which is in line with our cross-sectional asset

[8]While it is generally difficult to measure capital flows within financial conglomerates, Section 4.2.2 provides anecdotal evidence from the bankruptcies of Drexel Burnham Lambert in 1990 and Lehman Brothers in 2008. In these two cases, postmortem analysis by bank regulators revealed large capital transfers between broker-dealer holding companies in normal times and close to bankruptcy, in support of the idea that holding company leverage is the economically important one.

[9]The list of theory contributions includes Allen and Gale (1994), Basak and Cuoco (1998), Gromb and Vayanos (2002), Xiong (2001), Kyle and Xiong (2001), Vayanos (2004), Pavlova and Rigobon (2007), Brunnermeier and Pedersen (2009), Duffie (2010), Adrian and Shin (2010), Garleanu and Pederson (2011), Adrian and Boyarchenko (2012), Basak and Pavlova (2013), Gabaix and Maggiori (2015), among others.

pricing tests.

AEM is the first paper to provide systematic empirical support for intermediary asset pricing theory in equity and bond markets, using classic cross-sectional pricing tests. Adrian, Moench, and Shin (2014b) extends the AEM evidence by demonstrating that broker-dealer leverage has significant time-series forecasting power for returns on stocks and bonds. Haddad and Sraer (2015) argue that banks are central in understanding interest rate risk and document that banks' exposure to fluctuations in interest rates forecasts excess Treasury bond returns.

Equity markets see greater direct participation by households. Participation of households in less sophisticated markets in no way precludes financial intermediaries from also being marginal, so that the intermediary kernel may price assets in these markets as well.[10] In more specialized asset classes, on the other hand, trading is dominated by intermediaries, hence their pricing kernel should be more robust for sophisticated asset classes than in equities. Past work has shown direct evidence linking the behavior of intermediary capital to security prices in these sophisticated asset classes. Early work by Froot and O'Connell (1999) studies the effects of slow-moving intermediary capital in the catastrophe insurance market. Gabaix et al. (2007) study the mortgage-backed securities market, and present evidence that the marginal investor pricing these assets is a specialized intermediary rather than a CAPM-type representative household. Bates (2003) and Garleanu, Pedersen, and Poteshman (2009) provide similar evidence for index options, and Chen, Joslin, and Ni (2016) infer the tightness of intermediary constraints from the quantities of option trading, and further link it to high risk premia for a wide range of financial assets. Mitchell et al. (2007) provide a range of pricing distortions in certain asset markets—including convertible bond arbitrage and merger arbitrage—when arbitrageurs that specialize in these assets suffer significant losses in capital. Mitchell and Pulvino (2009) offer further evidence on the divergent behavior of the bond-CDS basis during the 2008 financial crisis. Siriwardane (2015) demonstrates the effect of intermediary capital losses on CDS spreads. In exchange rate literature, Adrian, Etula, and Shin (2009), Adrian, Etula, and Groen (2011), and Hong and Yogo (2012) show that financiers' positions are useful in predicting expected currency returns, a fact that is consistent with the broad view proposed by

[10] Conceptually, if households are marginal investors in equity and bond markets and households' pricing kernel is accurately measured, it should also succeed in pricing the cross section of equities and bonds, regardless of the presence of intermediaries as additional marginal traders in the market. The daunting task facing the household view is constructing a pricing kernel from relatively poor quality household data.

our paper. Verdelhan, Du, and Tepper (2016) study persistent violations of covered interest parity and link this to financial constraints faced by dealers. Perhaps the most important contribution of our paper is to formally and simultaneously test the intermediary model in a wide range of asset classes where we expect intermediaries to matter most and households to matter least.

2 Intermediary Capital Risk in a Two-factor Asset Pricing Model

We propose a two-factor model in which the intermediary's equity capital ratio enters the pricing kernel alongside aggregate wealth. Section 2.1 provides an argument for why this specification captures the intermediary's marginal value of wealth and thus why it prices all asset classes in which the intermediary participates as a marginal investor. There are various economic mechanisms for why and how the intermediary's capital ratio affects its marginal value of wealth, and Section 2.2 lays out one such theory based on He and Krishnamurthy (2012).

2.1 Intermediary capital ratio and pricing kernel

Traditional consumption-based asset pricing models (Campbell and Cochrane, 1999; Bansal and Yaron, 2004) are cast in a complete market where the marginal investor is a consumer household. These models implicitly view intermediation as a pure pass through, and asset markets are studied as direct interactions among households. By contrast, intermediary asset pricing models emphasize the unique role that sophisticated intermediaries play in many risky financial assets. These models short circuit the aggregation arguments that lead to representative household models by limiting the participation of households in certain markets and introducing frictions in the ability of "specialist/expert" intermediaries to raise financing from the household sector. As a result, households are *not* marginal in at least some markets, and household marginal utility of consumption fails to price assets in those markets. For these same markets, intermediaries take over the role of marginal trader, raising the possibility that their marginal value of wealth is better suited as an empirical pricing kernel.

We propose the following intermediary pricing kernel, in which the equity capital ratio of the intermediary sector determines its marginal value of wealth. We define the intermediary's (equity) capital ratio as the equity fraction of total assets in the aggregate balance sheet of the intermediary sector:

$$\eta_t \equiv \frac{\text{Equity}_t}{\text{Asset}_t}. \tag{1}$$

Denote aggregate wealth in the economy by W_t. We define the intermediary's marginal value of wealth at time t as

$$\Lambda_t \propto e^{-\rho t} \cdot (\eta_t W_t)^{-\gamma}, \tag{2}$$

where $\rho > 0$ and $\gamma > 0$ are positive constants, which we later show correspond to the intermediary's time-discount rate and relative risk-aversion, respectively.

The empirical study in this paper relies on the qualitative implications of (2), but not on the specific functional form. The exact functional form in (2), which arises from existing theories under appropriate assumptions, is intuitive. First, the aggregate wealth term W_t captures the asset pricing role of persistent productivity shocks that affect the overall fundamentals of the economy. It is the standard economic growth term in consumption-based theories and has the same interpretation here—all else equal, W_t is negatively related to the economic agent's marginal value of wealth.

The second and more novel aspect of intermediary asset pricing models is the role of η_t. Specification (2) implies that the intermediary's marginal value of wealth rises when the intermediary's capital ratio η_t falls. It captures the intuition that an intermediary's risk bearing capacity is inhibited when its equity capital is low. Risk aversion drives up the intermediary's marginal value of wealth in low equity states. This theoretical mechanism operates in the micro foundation of Section 2.2 as long as a significant portion of the compensation received by managers/traders is stock-based. Importantly, there are other potential mechanisms that lead intermediaries to value a dollar more when their (equity) capital is impaired. For institutions that face regulatory capital requirements, risk-tolerance shrinks as losses eat into their capital base, leading them to potentially forgo otherwise profitable investment opportunities. An extra dollar of capital is especially valuable to the institution in these states.[11]

To summarize, the marginal value of wealth specification in (2) has a two-factor structure that embeds the broad economic growth shocks of traditional models via W_t, along with shocks

[11] Many of the largest primary dealers in our sample are constrained by Basel capital requirements (Kisin and Manela, 2016), and potentially also by the SEC's net capital rule. Capital constraints are particularly costly during liquidity crises (Kashyap, Rajan, and Stein, 2008; Hanson, Kashyap, and Stein, 2011; Koijen and Yogo, forthcoming; Kisin and Manela, 2016).

that govern soundness of the financial intermediary sector via η_t. This second factor captures agency/contracting frictions in the intermediation business, regulator considerations, or shocks to non-dealer portions of the intermediary's portfolio (e.g., the mortgage market collapse in 2007-09) that affect the intermediary's broader risk bearing capacity.[12] This two-factor view is consistent with Muir (2014) who shows that asset pricing behavior is markedly different during fundamental disasters (such as wars) and financial disasters (such as banking panics).

Given (2), we use the asset pricing Euler equation to derive the two-factor asset pricing model that is the basis of our cross-sectional tests. For any asset i with instantaneous return dR_t^i, the first-order condition of the intermediary who acts as the marginal investor implies

$$\mathbb{E}_t\left(dR_t^i\right) - r_t^f dt = -\mathbb{E}_t\left(dR_t^i \cdot \frac{d\Lambda_t}{\Lambda_t}\right),$$

where throughout $\mathbb{E}_t(\cdot)$ stands for conditional expectations and r_t^f is the risk-free rate. This further implies

$$\begin{aligned}\mathbb{E}_t\left(dR_t^i\right) - r_t^f dt &= \gamma\mathbb{E}_t\left[dR_t^i \cdot \frac{dW_t}{W_t}\right] + \gamma\mathbb{E}_t\left[dR_t^i \cdot \frac{d\eta_t}{\eta_t}\right] \\ &= \beta_{W,t}^i dt \cdot \lambda_W + \beta_{\eta,t}^i dt \cdot \lambda_\eta. \end{aligned} \tag{3}$$

The term $\lambda_W \equiv \gamma\sigma_{W,t}^2 > 0$ is the price of risk on aggregate wealth shocks (or "market risk") and $\lambda_\eta \equiv \gamma\sigma_{\eta,t}^2 > 0$ is the price of intermediary capital risk, where we use the standard notation for beta in a multivariate regression setting:

$$\begin{bmatrix} \beta_{W,t}^i \\ \beta_{\eta,t}^i \end{bmatrix} = \begin{bmatrix} \mathbb{E}_t\left(\frac{dW_t}{W_t}\right)^2 & \mathbb{E}_t\left(\frac{dW_t}{W_t}\cdot\frac{d\eta_t}{\eta_t}\right) \\ \mathbb{E}_t\left(\frac{dW_t}{W_t}\cdot\frac{d\eta_t}{\eta_t}\right) & \mathbb{E}_t\left(\frac{d\eta_t}{\eta_t}\right)^2 \end{bmatrix}^{-1} \cdot \begin{bmatrix} \mathbb{E}_t\left[dR_t^i \cdot \frac{dW_t}{W_t}\right] \\ \mathbb{E}_t\left[dR_t^i \cdot \frac{d\eta_t}{\eta_t}\right] \end{bmatrix}.$$

Equation (3) is the two-factor pricing model that guides our cross-sectional pricing tests, and in particular predicts that the price of both market risk and intermediary capital risk are positive. The intuition behind the prediction is that a positive shock to either W_t or η_t drives down the

[12] For example, He and Krishnamurthy (2012) (page 757, Section 4.4.5) consider a setting in which the second shock affects the severity of agency problems when intermediaries contract with households. In equilibrium, a negative shock to agency frictions lowers the households' equity capital contribution, which drives the evolution of leverage and hence the pricing kernel in (2).

marginal value of wealth Λ_t; hence, the higher an asset's covariance with either factor, the higher the expected equilibrium return that the asset must promise to compensate its investor.

2.2 An intermediary asset pricing model

We now provide a theoretical framework where the exact intermediary pricing kernel in (2) arises in general equilibrium. Consider a two-agent economy populated by households and financial intermediaries. Suppose that the intermediary (or, the specialist/expert who runs the intermediary in the language of He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014)) has power utility over its consumption stream

$$\mathbb{E}\left[\int_0^\infty e^{-\rho t} u\left(c_t\right) dt\right] = \mathbb{E}\left[\int_0^\infty e^{-\rho t} \frac{c_t^{1-\gamma}}{1-\gamma} dt\right],$$

with ρ being the discount rate and γ being the constant relative risk aversion.

Since intermediaries (rather than households) are always marginal investors in risky assets, their marginal utility of wealth, which equals the marginal utility of consumption, prices all assets in equilibrium.[13] To a first-order approximation, the intermediary's consumption c_t is proportional to its wealth W_t^I. That is, $c_t = \beta W_t^I$, where β is a positive constant. For log utility this simple consumption rule is exact with $\beta = \rho$. Hence the intermediary's discounted marginal utility of consumption is

$$\Lambda_t = e^{-\rho t} u'\left(\beta W_t^I\right) = e^{-\rho t}\left(\beta W_t^I\right)^{-\gamma}. \tag{4}$$

It is the intermediary's wealth W_t^I (or the bankers' net worth, in connection to the macro finance literature) that enters directly into the pricing kernel.

Let aggregate wealth, W_t, include the wealth of both the household and intermediary sectors, and define η_t as the intermediary sector's share of aggregate wealth in the economy:

$$W_t^I = \eta_t W_t. \tag{5}$$

That is, the intermediary's wealth share is directly linked to the its level of capital, and captures

[13] We need not specify the utility function of households as the intermediary's optimality condition yields the pricing relations that we take to data.

the soundness of the intermediary sector in this economy.

This brings us back to our definition of the intermediary capital ratio in Section 2.1, $\eta_t = \frac{\text{Equity}_t}{\text{Assets}_t}$. Under stylized assumptions, the intermediary's capital ratio exactly coincides with its wealth share. For instance, He and Krishnamurthy (2012, 2013, 2014) assume that risky assets are held directly only by the intermediary sector.[14] Then, in general equilibrium, equity measures the intermediary's net worth and assets on the intermediary balance sheet measure aggregate wealth, thus the capital ratio indeed measures the wealth share of the intermediary sector.[15] Therefore, plugging (5) into (4) arrives at the pricing kernel in Equation (2).

We emphasize, though, that our reduced form cross-sectional asset pricing tests only rely on qualitative properties of the pricing kernel, and hence this stringent assumption about asset holdings can be easily relaxed (e.g., Brunnermeier and Sannikov (2014)). For the pricing kernel specification (2) to price assets, we require that the intermediary's capital ratio is positively correlated with its wealth share η_t. This key property holds in Brunnermeier and Sannikov (2014), which allows households to manage risky assets at some exogenous holding cost.[16]

3 Cross-Sectional Analysis

We present our main empirical results in this section. After explaining the data construction, we perform formal cross-sectional asset pricing tests for a variety of asset classes.

3.1 Data

3.1.1 Primary dealers' market equity capital ratio

Our definition of the intermediary sector is the set of *primary dealers*. These form a select group of financial intermediaries that serve as trading counterparties to the Federal Reserve Bank of New

[14] Although the assumption in He and Krishnamurthy (2012, 2013) appears rather stark, it is consistent with He et al. (2010) who document that mortgage-related toxic assets are always on the balance sheet of financial intermediaries (mainly commercial banks) at the height of the crisis, 2008Q4 to 2009Q1.

[15] In He and Krishnamurthy (2012, 2013), households can also access risky assets indirectly through the intermediary sector with certain agency frictions, which could bind (the "constrained" region) or not (the "unconstrained" region). This mapping between η_t and the capital ratio is exact in the constrained region.

[16] In Brunnermeier and Sannikov (2014), a series of negative shocks impairs the capital of intermediaries, leading them to reduce their borrowing and sell assets to households. Nevertheless, debt reduction lags behind the pace of equity impairment, and the endogenous capital ratio of the intermediary sector falls following negative shocks. As a result, the intermediaries' wealth share η_t moves together with their capital ratio.

York in its implementation of monetary policy. We obtain the historical list of primary dealers from the NY Fed's website, and hand-match dealers to data on their publicly-traded holding companies from either CRSP/Compustat (for US dealers) or Datastream (for foreign dealers). We list current primary dealer designees in Table 1 and provide the full historical list in Table A.1.[17]

The primary dealer sector is a natural candidate for the representative financial intermediary. These institutions are large and active intermediaries who are likely to be marginal in almost all financial markets. Table 2 shows that this relatively small group of firms represents essentially all of the broker-dealer sector by size, a substantial share of the broader banking sector, and is even significant relative to the entire publicly traded sector.[18] Below, "primary dealer" and "intermediary" are used interchangeably whenever there is no ambiguity in the context.

Each quarter t, we construct the (aggregate) primary dealer capital ratio as

$$\eta_t = \frac{\sum_i \text{Market Equity}_{i,t}}{\sum_i \left(\text{Market Equity}_{i,t} + \text{Book Debt}_{i,t}\right)} \tag{6}$$

where firm i is a NY Fed primary dealer designee during quarter t.[19] Our data inputs for the capital ratio come from the quarterly CRSP/Compustat file for US firms. Book value of debt is equal to total assets less common equity, using the most recent data available for each firm at the end of a calendar quarter. The market value of equity is share price times shares outstanding on the last trading day of the quarter. We follow the same calculation with Datastream data for public holding companies of foreign primary dealers.

Two comments are in order regarding the way we construct the primary dealer capital ratio in (6). We use market values of equity, because market values are arguably better at reflecting the financial distress of intermediaries. Due to data availability, we use book values of debt to proxy for unobserved market values of debt, as customary in the empirical corporate finance literature that studies the capital structure of non-financial firms (Leary and Roberts, 2005). This approximation

[17] Cheng, Hong, and Scheinkman (2015) focus on primary dealers in their study of executive compensation in financial firms.

[18] For comparison, we focus on US-only firms in Table 2, and define the total broker-dealer sector as the set of US primary dealers plus any firms with a broker-dealer SIC code (6211 or 6221). Note that had we instead relied on the SIC code definition of broker-dealers, we would miss important dealers that are subsidiaries of holding companies not classified as broker-dealers, for instance JP Morgan.

[19] We study the market capitalization-weighted average capital ratio of primary dealers. When we instead study the equal weighted average capital ratio our results are very similar.

is even more convincing in our context of financial firms. As mentioned, we are measuring the capital structure of primary dealers' holding companies, which are often large banking institutions. One salient feature of banking institutions, as a business model, is that the majority of their liabilities consist of safe short-term debt such as deposits, repurchase agreements (repo), and trading liabilities which are to a large extent collateralized. Unlike industrial firms whose debt could be risky following adverse shocks, low risk short-term debt is relatively insensitive to the firm's credit risk as well as credit risk premium fluctuations. Therefore, our book value approximation for debt is likely accurate.[20]

Second, in (6) we first aggregate the balance sheets of the primary dealer sector, and then calculate the capital ratio for the aggregated sector (i.e., a value-weighted average of dealers' capital ratios). Alternatively, one could calculate the capital ratio for individual dealer first, and then aggregate with equal weights. This touches on the important question: how should one aggregate individuals' pricing kernels in an economy with potentially heterogeneous economic agents? In Section 3.2.5, we explain why it is more appealing to use a value-weighted average in our setting.

We plot the intermediary capital ratio, which runs from 1970 to 2012, in Figure 1 (with shaded areas indicating NBER recessions). Intermediary capital falls during recessions and reaches its nadir in the 2008 financial crisis. The capital ratio also exhibits a sudden drop and rebound around the 1998 LTCM collapse, representing shocks that only affect certain asset markets (e.g., options) but not the entire stock market.

We construct the capital ratio growth rate, denoted η_t^{Δ}, as follows. We estimate a shock to the capital ratio in levels, u_t, as an innovation in the auto-regression $\eta_t = \rho_0 + \rho\eta_{t-1} + u_t$,[21] and convert this to a growth rate (as suggested by equation (3)) by dividing by the lagged capital ratio

$$\eta_t^{\Delta} = u_t/\eta_{t-1}.$$

This serves as the risk factor that is the key input into our cross section tests.

Figure 1 plots η_t and η_t^{Δ}, and Table 3 shows their correlations with an array of aggregate macro variables. Specifically, we compare to the S&P 500 earnings-to-price ratio from Shiller,

[20] According to JPMorgan's FY 2006 annual report, 76.8% of its liabilities consists of deposits, repo, and trading liability which can be considered as absolutely safe. Long-term debt, which is counted as loss-absorbing liability and hence subject to credit risk, is only about 11.8%. Balance sheets of the other large primary dealers are similar.

[21] The estimated quarterly AR(1) coeffcient is 0.94.

the unemployment rate, GDP growth, the Chicago Fed National Financial Conditions Index (for which a high level corresponds to weak financial conditions), and realized volatility of the CRSP value-weighted stock index. Correlations with η_t^{Δ} are based on log changes in each macro variable. All correlations reflect pro-cyclicality of the capital ratio (or counter-cyclicality of leverage) in that low intermediary capital growth coincides with adverse economic shocks, measured as increases in the earnings-to-price ratio, increases in the unemployment rate, decreases in GDP growth, a deterioration in financial conditions (based on the Chicago Fed index), or increases in realized volatility.

3.1.2 Asset portfolios

A key feature distinguishing our paper from existing literature is our use of test portfolios that span a wide range of asset classes. To avoid potential arbitrariness or data mining concerns in our choice of test portfolios, especially for asset classes that are less standard than the Fama-French equity data, we rely on readily available asset portfolios provided by authors of pre-existing studies wherever possible.

For equities, we use the Fama and French (1993) 25 size and value sorted portfolios (from Ken French's website). For US bonds, we include government and corporate bond portfolios in the same class.[22] We use ten maturity-sorted government bond portfolios from CRSP's "Fama Bond Portfolios" file with maturities in six month intervals up to five years. For corporate bonds, we use ten portfolios sorted on yield spreads from Nozawa (2014). These portfolios are based on a comprehensive bond data set combining TRACE, the Lehman bond database, and others, starting in 1973.

For sovereign bonds we use six portfolios from Borri and Verdelhan (2012). These portfolios are based on a two-way sort on a bond's covariance with the US equity market return and the bond's Standard & Poor's credit rating. Monthly portfolio returns begin in January 1995 and end in April 2011.

For options, we use 54 portfolios of S&P 500 index options sorted on moneyness and maturity from Constantinides, Jackwerth, and Savov (2013), split by contract type (27 call and 27 put

[22]Our choice to combine US government and corporate bonds into a single asset class is driven by our desire to estimate prices of intermediary capital risk separately for each asset class. Treating US government bonds as its own asset class is not statistically sensible due to the very high correlation in the returns on these portfolios.

portfolios), and starting in 1986. Portfolio returns are leverage-adjusted, meaning that each option portfolio is combined with the risk-free rate to achieve a targeted market beta of one. According to Constantinides et al. (2013), "*The major advantage of this construction is to lower the variance and skewness of the monthly portfolio returns and render the returns close to normal (about as close to normal as the index return), thereby making applicable the standard linear factor pricing methodology.*" To keep the number of portfolios used in our tests similar across asset classes, we reduce the 54 portfolios to 18 portfolios by constructing equal-weighted averages of portfolios that have the same moneyness but different maturity (though our results are essentially unchanged if we use all 54 portfolios separately).

For foreign exchange, we combine two datasets of currency portfolios to arrive at a total of twelve portfolios. First is the set of six currency portfolios sorted on the interest rate differential from Lettau, Maggiori, and Weber (2014). Second is the set of six currency portfolios sorted on momentum from Menkhoff, Sarno, Schmeling, and Schrimpf (2012). We use the sample period intersection of these datasets, covering March 1976 to January 2010.[23]

For commodities, we use returns to commodity futures from the Commodities Research Bureau.[24] We begin from the list of 31 commodities in Table 1 of Yang (2013). For each commodity, we form an equal-weighted portfolio of all futures contracts with maturities up to four months. These 31 commodities differ in their availability, with some samples only available for a few years. To balance the benefits of a long sample and many commodities, we include in our dataset 23 commodity portfolios with at least 25 years of returns data.[25]

For CDS, we construct 20 portfolios sorted by spreads using individual name 5-year contracts. The data are from Markit and begin in 2001. We focus on 5-year CDS for the well known reason that these are the most liquid contracts. Our definition of CDS returns follows Palhares (2013). In particular, let CDS_t be the credit spread at day t. The one-day return on a short CDS strategy

[23] We use combined data because the underlying data sources for the two sets of portfolios differ somewhat and the portfolio correlations are relatively low. Multiple regression of each Lettau et al. portfolio on to all six Menkhoff et al. portfolios yields R^2s of 0.53, 0.74, 0.82, 0.81, 0.75, and 0.56. Since these portfolios are far from collinear, our tests benefit from improved power by doubling the number of portfolios. However, the qualitative results of our tests are identical if we restrict our currency analysis to only one of the two data sets.

[24] This same data set is used by Yang (2013) and Gorton, Hayashi, and Rouwenhorst (2013) to study the behavior of commodity returns.

[25] In an earlier draft of this paper, we studied an alternative dataset of 24 commodity futures return indices studied in Koijen, Moskowitz, Pedersen, and Vrugt (2013), which begins substantially later than the Commodities Research Bureau dataset. Nonetheless, the commodity results in that earlier analysis were very similar to the results we report here.

(in the case of no default) is

$$CDS_t^{ret} = \frac{CDS_{t-1}}{250} + \triangle CDS_t \times RD_{t-1}.$$

The first term on the right-hand-side is the carry component of the return due to the seller's receipt of insurance premium payments. The second term is the capital gain return, equal to the change in spread times the lagged risky duration of the contract (denoted RD_{t-1}). The risky duration capitalizes the future per-period CDS spread that a seller receives into a present value, which when multiplied by the change in spread approximates the log capital gain of the short position.[26]

We also consider tests in which all portfolios are gathered into a single large cross-section. Because some asset classes (such as CDS) are only available toward the end of our sample, the tests of all portfolios use an unbalanced panel of portfolio returns.

Table 4 provides summary statistics by asset class. For each class, we report the average portfolio excess return and time series beta with respect to each risk factor. Importantly for our tests, we observe considerable risk dispersion within and across asset classes. For example, the standard deviation of the time-series intermediary capital beta (β_η) across the 25 Fama-French portfolios is 0.11, or 1.5 times its mean of 0.07. The last two columns show that in the pool of all asset classes the dispersion in β_η is even higher, with a standard deviation that is 11 times its mean. The p-values of the χ^2 statistics show that betas are jointly significantly different from zero in each of the asset classes.

[26] The risky duration for CDS of maturity M years with quarterly premium payments is computed as

$$RD_t = \frac{1}{4}\sum_{j=1}^{4M} e^{-j\lambda/4} e^{-j(r_t^{j/4})/4}$$

where $e^{-j\lambda/4}$ is the quarterly survival probability, $r_t^{j/4}$ is the risk-free rate for the quarter $j/4$, and $e^{-j(r_t^{j/4})/4}$ is the quarterly discount function. In the empirical implementation we assume that the term structure of survival probabilities is flat and extract λ each day from the 5-year spread as $\lambda = 4\log(1 + CDS/4L)$, where CDS is the spread and L is the loss given default (assumed to be 60%). The risk-free term structure is constructed using swap rates for maturities 3 and 6 months and US Treasury yields for maturities from 1 year to 10 years (data from Gürkaynak, Sack, and Wright, 2007). Risk-free rates are interpolated with a cubic function to find rates for each quarter.

3.2 Cross-sectional asset pricing tests

We turn next to formal cross-sectional asset pricing tests. These assess whether differential exposure to intermediary capital shocks across assets can explain the variation in their expected returns. We investigate each asset class separately, and also conduct joint tests using the full universe of asset classes together.

3.2.1 Estimated price of intermediary capital risk across asset classes

Our investigation of these seven asset classes begins with cross-sectional asset pricing tests in each class separately. For each portfolio i in asset class k, we estimate betas from time-series regressions of portfolio excess returns, $R_{t+1}^{i_k} - r_t^f$, on the intermediary capital risk factor, η_{t+1}^{Δ}, and on the excess return of the market portfolio, $R_{t+1}^{W} - r_t^f$:[27]

$$R_{t+1}^{i_k} - r_t^f = a^{i_k} + \beta_\eta^{i_k}\eta_{t+1}^{\Delta} + \beta_W^{i_k}\left(R_{t+1}^{W} - r_t^f\right) + \epsilon_{t+1}^{i_k}. \tag{7}$$

We then run a cross-sectional regression of average excess portfolio returns on the estimated betas within each asset class k in order to estimate the asset class-specific risk prices λ_η^k and λ_W^k:[28]

$$\hat{\mathbb{E}}\left[R_{t+1}^{i_k} - r_t^f\right] = \gamma_k + \lambda_\eta^k\hat{\beta}_\eta^{i_k} + \lambda_W^k\hat{\beta}_W^{i_k} + \nu^{i_k}. \tag{8}$$

The intermediary asset pricing literature emphasizes the non-linearity, i.e., the price of risk is state dependent and may rise during severe economic downturns. Note that under the assumption of constant asset beta, the unconditional estimate is an estimate of the average price of risk over time. We discuss the role of non-linearity in Section 5.3.

Our main focus is on the price of the intermediary capital risk, λ_η^k. Table 5 reports estimates for the 1970Q1–2012Q4 period. The first seven columns include results from independent estimation

[27] The model (3) is in the conditional form, while our empirical implementation uses an unconditional test. If test asset betas are constant over time, then the risk prices that we estimate are simply unconditional expectations of potentially state-dependent risk prices. If, however, the true betas are time-varying, then in general (7) and (8) are misspecified. The divergence between model and empirics is due to data limitations and for the sake of transparency. The conditional test requires an estimate of conditional betas, which is challenging due to the intermediary capital factor's reliance on quarterly accounting information (data limitations). This may be overcome with more sophisticated estimators and ad hoc specification of conditioning information, though we leave this for future research (sake of transparency).

[28] The cross section regressions in (8) include the constant γ_k. Section 5.6 reports estimation results that impose the model restriction $\gamma_k = 0$, which produces nearly identical results.

within each asset class. Below estimated risk prices we report GMM t-statistics that correct for cross-correlation and first-stage estimation error in betas. The measures of model fit that we report are the cross-sectional R^2 for average portfolio returns, and the related mean absolute pricing error (MAPE) in percentage terms (that is, the mean absolute residual in the cross-sectional regression multiplied by 100).

Intermediary capital risk price estimates are positive in all asset classes, supporting the main empirical prediction of our proposed pricing kernel. Risk price estimates range from 7% for equities to 22% for options, and are statistically significant in all but two asset classes at the 5% level, and in all classes at the 10% level (the t-statistic is 1.66 for sovereign bonds and 1.90 for commodities). The model provides the closest fit for option portfolios (R^2 of 99%) and the weakest fit for commodities (R^2 of 25%).

The last column of Table 5 reports results when all 124 portfolios from seven asset classes are included simultaneously in the cross-sectional test. The estimated price of intermediary capital risk is 9.35% per quarter with a t-statistic of 2.56 and R^2 of 71%. This risk price estimate is economically large. For example, the cross-sectional standard deviation in intermediary capital growth betas for the all portfolios case is 0.11 (see Table 4). Thus, a one standard deviation difference in the capital risk beta of two assets corresponds to a difference of $0.11 \times 9.35 \times 4$, or 4.11 percentage points, in their annual risk premia. We also report a restricted MAPE-R, which uses the pricing errors for each asset class, but where the risk prices are restricted to those of the all portfolios cross-sectional regression. Comparing these MAPE-R estimates to MAPEs, shows modest economic gains, in terms of pricing ability, from allowing risk prices to vary across asset classes.[29]

Quite interestingly, the estimated price of risk on the market portfolio is positive in all asset classes, though it is significant only in the FX test. The significance of intermediary capital risk after controlling for the market return indicates that our pricing kernel statistically improves on the CAPM for all sets of test assets. In Section 3.2.3, we show that capital risk remains a powerful determinant of asset price behavior after controlling for other standard risk factors.

[29] Figure 2 plots average portfolio returns in all asset classes versus predicted values from the two-factor intermediary capital model. Appendix Table A.1 draws the same plot using separate parameter estimates within each asset class. In untabulated tests, we standardize portfolio returns by the average volatility of portfolios within its asset class, which equalizes the variance contribution of each asset class in the all portfolios test. The resulting capital risk price estimate is 10.91 (t-statistic of 3.09). Similarly, if we assign each portfolio a weight that is inversely proportional to the number of test assets in that portfolio's asset class, which equalizes the contribution of each asset class to the test in terms of observation count, the price of risk is 9.60 (t-statistic of 3.44), again corroborating our main result.

3.2.2 Are prices of risk similar across asset classes?

The *sign* of the estimated price of risk for intermediary capital factor is consistently positive across all asset classes in Table 5. What can we learn from the magnitudes of the estimates?

Under the standard asset pricing theoretical framework, if (2) is indeed an appropriate pricing kernel for all assets, then the price of risk from each asset class should be the same (up to sampling error). This is trivially evident from the Euler equation, which implies that risk prices are independent of the specific asset in question:

$$\mathbb{E}_t\left(dR_t^{i_k}\right) - r_t^f dt = \beta_{\eta,t}^{i_k} dt \cdot \underbrace{\gamma\sigma_{\eta,t}^2}_{\lambda_\eta} + \beta_{W,t}^{i_k} dt \cdot \underbrace{\gamma\sigma_{W,t}^2}_{\lambda_W}, \text{ for all } i,k. \tag{9}$$

Intuitively, risk prices are determined solely by the pricing kernel of marginal investors; while the quantity of risk–or beta–is an attribute of the asset and can differ substantially across classes. Equation (9) makes the theoretical statement that any difference in risk premia across assets must come solely from differences in betas, holding risk prices fixed. If λ is for some reason higher in a particular asset class, then the intermediary can earn a higher expected return (without increasing its risk) by tilting its portfolio toward this class. In turn, prices of risk would equalize, reinforcing the equilibrium consistency of risk prices across all assets.

The test in the last column of Table 5, i.e., the "all" portfolios column, indeed imposes that risk prices are equal across asset classes. Figure 3 compares intermediary risk prices from different asset classes, and also compares with the all portfolios estimate, to illustrate the similarity in estimates across tests. Formally, our test cannot reject the hypothesis that the estimated risk price is equal to 9% per quarter (the value found in the all portfolios case) for *any* of the individual asset classes, at the 5% significance level. This is not merely a statement that our standard errors are large and lack power—we indeed reject the null of a 0% risk price in *all* classes (at the 10% significance level or better).

From a theory perspective, the prediction of equal risk prices relies on the following key assumptions. First, the proposed financial intermediary pricing kernel represents the intermediaries' marginal value of wealth. Second, financial intermediaries are actively making trading decisions in all asset markets (though not necessarily with large net positions). Also implicit in these assumptions is a degree of homogeneity in the pricing kernels of individual financial intermediaries. That all financial intermediaries are homogeneous is the most standard—but perhaps the most tenuous—of these assumptions. Its failure could potentially explain the somewhat higher options and FX point estimates, if intermediaries that specialize in trading these securities differ in some way from other intermediaries (see for example Gârleanu, Panageas, and Yu, 2015). We discuss heterogeneity among dealers in Section 3.2.5.

Irrespective the interpretation, comparing the magnitudes of the risk price estimates across markets is informative. One might expect that trading in different asset classes involves substantially different knowledge, expertise, and terminology; yet all of these markets produce estimated prices of intermediary capital risk with similar magnitude. This result is broadly in line with the assumption of homogeneity among intermediaries, but also consistent with the premise that the marginal intermediaries are different in each asset class but nonetheless all have highly correlated capital ratios (and hence the discrepancy of estimated risk prices is small).

The central reason we include equity (more specifically, Fama and French (1993) 25 size and value sorted portfolios) is to remain comparable with recent empirical work in intermediary asset pricing, as well as the vast literature on US equity pricing. But we deem that equity is the asset class that is *least* likely to be explained by the pricing kernel of primary dealers. Section 5.7 provides suggestive evidence that these large banking-oriented financial institutions are not obviously active in (and hence unlikely to be marginal traders in) equity markets; this contrasts starkly with their large activity in other more sophisticated asset classes that are essentially all over-the-counter markets. Section 5.7 also reports more detailed asset pricing robustness tests that focus on additional widely-used equity portfolios such as momentum and international equity.

3.2.3 Is the intermediary capital factor just a proxy for other pricing factors?

A large literature has investigated factors that explain the cross section of asset returns. These analyses focus on the pricing of US equities, and have not been tested as pricing factors in many of the asset classes we study. Our intermediary capital factor is not a proxy for commonly studied factors in US equity markets.

In Table 6, we compare the pricing power of our intermediary capital ratio factor relative to the CAPM, the Fama and French (1993, 2015) three- and five-factor models, the momentum factor, the Pástor and Stambaugh (2003) liquidity factor, and the Lettau et al. (2014, LMW) downside risk CAPM. The table reports the cross section R^2 and MAPE with and without the intermediary capital factor. Including the intermediary capital factor improves the cross-sectional R^2 in the "all" portfolios test by 15% and reduces the MAPE by 27% relative to the Fama-French five-factor model. In all cases, the estimated price of intermediary capital risk is essentially unchanged by inclusion of other commonly studied factors, and remains statistically significant.[30]

The LMW model is arguably the most relevant benchmark as it appears to price well across various assets classes. Absent the capital ratio risk factor, the downside beta in the LMW model has a large, significant role in explaining cross-sectional differences in average returns for our sample, consistent with the main finding in Lettau et al. (2014, LMW). However, once we account for exposures to intermediary capital shocks, the risk price on LMW downside beta becomes insignificant, while the price of risk on our capital risk factor is 7.56% and significant at the 10% level.

3.2.4 Are primary dealers special?

We next explore the role of our specific intermediary sector definition for the preceding results. We conduct placebo tests that replicate our cross section analysis, but replace the capital ratio of primary dealers with that of other "intermediary" definitions.

First, we consider defining intermediaries according to SIC codes of US broker-dealers—codes 6211 ("security brokers, dealers, and flotation companies") and 6221 ("commodity contracts brokers and dealers")—but exclude firms that are designated NY Fed primary dealers. This definition, which we refer to as "non-primary dealers," includes firms like Blackrock, Charles Schwab, and Waddell & Reed. As shown in Table 2, non-primary dealers tend to be smaller, standalone broker-dealers with little activity in derivatives markets.

In Panel (a) of Table 7, we report cross section tests using non-primary dealer capital ratio as a factor. Only equities and CDS show a significantly positive price of capital ratio risk based on this intermediary definition; the estimated price of capital risk in other asset classes is either

[30]Because our capital ratio factor is non-traded and theoretically motivated, statistically oriented models such as the Fama-French three and five-factor models are not natural benchmarks for comparison. In the words of Cochrane (2005), "*it is probably not a good idea to evaluate economically interesting models with statistical horse races against models that use portfolio returns as factors.... Add any measurement error, and the economic model will underperform its own mimicking portfolio. And both models will always lose in sample against ad hoc factor models that find nearly ex post efficient portfolios.*" Nonetheless, some readers may find the comparison is informative.

insignificant or has a negative sign.

Extending this idea further, we construct the equity capital ratio risk factor for the entire US non-bank sector, i.e., all public firms in CRSP/Compustat with SIC codes that do not begin with 6. The results, reported in Panel (b), demonstrate the overall inability of the non-bank capital ratio to price assets, with estimates switching sign across classes and a point estimate of nearly zero in the all portfolios test. Overall, Table 7 provides additional indirect evidence supporting our assumption that primary dealers are pricing-relevant financial intermediaries.

3.2.5 Heterogeneity within broker-dealer sector

The intriguing fact that the capital ratio of primary dealers–but not that of non-primary dealers–has strong explanatory power across asset markets is suggestive of heterogeneity within the broker-dealer sector. Theory typically imposes homogeneity within the intermediary sector, an assumption that provides the foundation for the sector-level pricing kernel in (6). Homogeneity is a theoretical abstraction. For empirical work, there is a trade-off. The narrower the definition of the intermediary sector, the more likely that the homogeneity assumption holds, but also the smaller and hence less likely the sector to be active on a wide range of asset markets. We seek balance between these two considerations.

Like AEM, we focus on the broker-dealer sector; but we zoom-in further and emphasize primary dealers in particular. In contrast to non-primary dealers, primary dealers are the largest broker-dealers and dominate almost all financial markets, so our definition continues to include the most economically important intermediaries. Interestingly, there is a much higher degree of homogeneity within the group of primary dealers, which supports our treatment of this group as a representative intermediary. For instance, the equal-weighted average capital ratio for primary dealers shares a 97.8% correlation with the value-weighted measure; in contrast, this correlation is only 56% for non-primary dealers.[31] More importantly, the leverage dynamics of primary dealers is quite different from that of non-primary dealers: the correlation between the value-weighted capital ratio of primary dealers and that of non-primary dealers is -9%. This is consistent with Table 2 which shows that primary dealers are indeed special in pricing assets across a range of financial markets.

[31] The median pairwise correlation in capital ratios of individual primary dealers is 58% for the 20 dealers that are in our sample for at least 20 years. For non-primary dealers, the median pairwise correlation in capital ratios is 44% for the 10 dealers that are in our sample for at least 20 years.

Despite the high similarity among primary dealers, these institutions are not identical. So what is the right way to aggregate information about potentially heterogeneous dealers' pricing kernels? More specifically, which average makes more sense, value-weighted or equal-weighted? Consider the most relevant theoretical benchmark, in which intermediaries are heterogeneous in their pricing kernels (marginal values of wealth), $\widetilde{m_i}$'s, where i indexes intermediaries, yet all are "marginal" investors so that in equilibrium their Euler equations are all satisfied. Then, it is easy to see that $\sum_i w_i \widetilde{m_i}$ is a valid pricing kernel for *any* weights $\{w_i\}$.[32] So, theories that favor one average over another must be some models in which some intermediaries are either not marginal investors in all markets, or at least not always marginal (see for example Gârleanu et al., 2015)

Our view is that a value-weighted average, which emphasizes larger broker-dealers, makes best economic sense. This is because it is natural to believe that all else equal, Euler equations errors are likely to be smaller for larger intermediaries. They are more likely to be active in all asset markets and they have more resources to exploit trading opportunities. Assigning greater weights to larger intermediaries is thus likely to attenuate potential pricing errors.

As a robustness check, Table 8 reports the same analysis as in Table 5, but uses the equal-weighted average capital ratio risk factor in place of our main measure. In most asset classes, the results are quantitatively unaffected, though somewhat weaker for US and Sovereign bonds. The capital ratio risk price estimated in the all portfolios case in fact rises slightly.

3.2.6 Which is more important for pricing, equity or debt of primary dealers?

Innovations in our measure of intermediary capital ratio are driven by either changes in equity or changes in debt, and now we investigate which of these is the more important driver of our asset pricing result.

We first show that our intermediary capital factor, which is approximately the shock to $\ln \eta_t =$

[32]Under this benchmark, we have $\mathbb{E}\left[\widetilde{m_i} \cdot \widetilde{R_j}\right] = 1$ for any dealer i and asset j. Then, for any weights $\{w_i\}$, one has

$$\mathbb{E}\left[\left(\sum_i w_i \widetilde{m_i}\right) \cdot \widetilde{R_j}\right] = \sum_i w_i \cdot \mathbb{E}\left[\widetilde{m_i} \cdot \widetilde{R_j}\right] = \sum_i w_i = 1 \text{ for any dealer } i \text{ and asset } j,$$

where the second equation uses the fact $\mathbb{E}\left[\widetilde{m_i} \cdot \widetilde{R_j}\right] = 1$. One caveat warrants discussion. In our context we focus on how to aggregate the capital ratio $\widetilde{\eta_i}$ for each intermediary, which is not directly its pricing kernel $\widetilde{m_i}$. Say $\widetilde{m_i} = g(\widetilde{\eta_i})$. Obviously, the result holds if $g(\cdot)$ is a linear function. Linearization is indeed our treatment in Equation (3) in the paper. When $g(\cdot)$ is a nonlinear function, if there is a non-random weighting vector $\{\hat{w}_i\}$ so that $g\left(\sum_i w_i \widetilde{\eta_i}\right) = \sum_i \hat{w}_i g(\widetilde{\eta_i})$, then the above result remains valid; but the exact condition is hard to characterize.

$\ln \frac{E_t}{E_t+D_t}$, can be decomposed into the growth rate of the primary dealer market equity, denoted by $d\ln E_t$, and the growth rate of their debt, denoted by $d\ln D_t$. More specifically, as we are only interested in diffusion terms (which implies that we can ignore Ito's correction terms which contribute to the drift), we have[33]

$$d\ln \eta_t = d\ln \frac{E_t}{E_t + D_t} = (1-\eta_t)\left(d\ln E_t - d\ln D_t\right). \tag{10}$$

As a result innovations, $d\ln \eta_t$, equal the equity growth rate shock $d\ln E_t$ minus the debt growth rate shock $d\ln D_t$, both scaled by $1-\eta_t$. Guided by (10), we test a three-factor version of our model that decomposes the capital risk factor into log innovations in primary dealer market equity and log innovations in their book value of debt. The decomposition in (10) also implies that the equity growth rate shock carries a positive price of risk, while the price of the debt growth rate shock should be negative.[34]

Because the primary dealer list changes over time, we construct equity and debt growth measures that are insensitive to entry and exit. The equity growth rate from quarter t to $t+1$ is defined as the log change in total market equity of all designated primary dealers as of time t. That is, if a designee enters the list in $t+1$, its equity is excluded from the $t+1$ growth rate calculation, and if it exits before $t+1$ then its market equity is still included in the growth rate (likewise for debt).[35] Besides, we continue to use the book value of debt to proxy for its market value, and this exacerbated measurement problem may bias us to find significant results on the debt growth factor.

The results are presented in Table 9, and the main take-away is that market equity is the more important component for our results, but that book debt plays a role in some cases as well. In all asset classes, the estimated price of risk on intermediary equity shocks remains positive and economically large (at least 5% per quarter in each asset class). For the all portfolios test, the price

[33]The derivation with intermediate steps is (recall $\eta_t = \frac{E_t}{E_t+D_t}$ and ignore drift terms with Ito corrections)

$$d\ln \eta_t = d\ln E_t - d\ln\left(E_t + D_t\right) = d\ln E_t - \frac{E_t d\ln E_t + D_t d\ln D_t}{E_t + D_t} = (1-\eta_t)\left(d\ln E_t - d\ln D_t\right).$$

[34]The capital ratio decomposition gives rise to an η_t term premultiplying the difference in equity growth and debt growth. This scales down the risk prices in this three-factor model relative to the benchmark model. But, because the time-series average of η_t is 0.06, this effect is quantitatively small, and risk price magnitudes can still be meaningfully compared to those in Table 9.

[35]We use this calculation to demonstrate that our findings are not driven by changes in the primary dealer list, though our results are unaffected if we allow entry and exit in our calculation.

of intermediary equity risk is 9% per quarter, which is the same as that of intermediary capital risk factor. Overall, the pricing ability of intermediary equity is similar, but statistically weaker, than that of the capital ratio variable. The estimated price on book debt innovations is negative in five out of seven asset classes, which is broadly consistent with our theory. While the estimated risk prices for debt growth are often insignificant, perhaps due to greater noise in book values, they are economically large for some asset classes like sovereign bonds and CDS.

4 Comparison with AEM: Empirics, Sample Composition, and Theory

AEM is an important precursor to our paper and is the first paper to bring the intermediary-based pricing paradigm into the conversation of "mainstream" empirical pricing models. These authors propose a one-factor intermediary pricing kernel. The factor is the innovation in broker-dealer book leverage derived from data in the Flow of Funds. In principle, the main intermediary leverage state variable in their empirical model is exactly the reciprocal of our capital ratio state variable. Though empirically, there are a number of important differences in our analyses that we discuss below.

AEM conduct standard cross section pricing tests using the twenty-five Fama-French equity portfolios, ten momentum equity portfolios, and six Treasury bond portfolios. The main result is the robust ability of broker-dealer leverage for pricing the cross section of stocks and Treasury bonds. They estimate a large and significant *positive* price of risk on *leverage* shocks. This has the interpretation that intermediary marginal value of wealth is higher when its leverage is lower, or equivalently implies that a high equity capital ratio indicates intermediary financial distress.

Due to the reciprocal relationship between capital ratio and leverage, AEM's finding is in direct contradiction with our finding of a robust *positive* price of risk price on the intermediary *capital ratio*. The AEM finding also contradicts the theoretical prediction of He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014) that a low capital ratio proxies for intermediary distress and hence a high marginal value of wealth.

The tension in the two sets of results is rather puzzling. Theoretically, we are attempting to measure the same quantity—financial distress of the intermediary sector—with the only conceptual difference being that their preferred measure is the inverse of our measure. Therefore, we would expect our price of risk estimates to always have the opposite sign, with otherwise similar magnitude and statistical significance. The facts are in stark contrast to this prediction. It stands to reason, therefore, that our empirical measures do not behave inversely to one another as predicted. Indeed, Figure 4a illustrates the inconsistency. Our capital ratio measure and AEM's leverage measure are significantly *positively* related in the time series, sharing a 42% correlation in levels. Figure 4b compares innovations in the two series, which share a 14% correlation.

We devote this section to understanding the differences in our empirical facts, and to place these differences in context of various intermediary asset pricing theories.

4.1 Empirical performance of AEM in many asset classes

First, we extend our multiple asset class tests to better understand the empirical performance of AEM's intermediary pricing kernel. This portion of our analysis is exactly analogous to our earlier tests using the capital ratio. In particular, we consider a two-factor model that includes AEM leverage innovations and the return on the market portfolio.[36]

Table 10 reports the estimated AEM leverage factor risk price and related model statistics for each asset class. For equities and US bonds, the AEM leverage factor carries a significantly positive price, which replicates the key findings reported by AEM (with the exception that our "US bonds" definition also includes corporates). In these two classes, the performance of the AEM pricing kernel is superior to ours, as reflected in their higher cross-sectional R^2. AEM also emphasize that their leverage measure successfully explains differences in average returns among momentum-sorted equity portfolios. Our measure, on the other hand, does not explain the momentum anomaly in equities.

The AEM model delivers very different results in other assets classes. The leverage risk price either becomes strongly negative (options, CDS, and FX) or remains positive but statistically insignificant (foreign sovereign bonds and commodities). In the all portfolios joint test, the estimated price of risk is positive but statistically insignificant. Furthermore, the estimated risk price of 12% is economically smaller. From Table 11, the standard deviation in AEM leverage betas across all portfolios is 0.05, implying differences in annual AEM leverage premia of $0.05 \times 12 \times 4$, or 2.4

[36]We construct the AEM leverage factor for the 1970–2012 period as described in their paper. It is 0.99 correlated with the one provided by Tyler Muir at `faculty.som.yale.edu/tylermuir/LEVERAGEFACTORDATA_001.txt`, which ends in 2009.

percentage points, for a one standard deviation difference in beta (or sixty percent of the risk premium effect that we find for our intermediary capital factor). Figure 5 illustrates the extent of inconsistency in AEM pricing performance across asset classes, which contrasts with the capital ratio model results in Figure 3.[37]

Our emphasis on a variety of asset classes—especially those relatively "exotic" ones like options, CDS, and FX—is the key empirical feature that distinguishes our paper from AEM; as mentioned in Section 3.2.2, equity is the asset class where we least expect to find good performance of the pricing kernel of primary dealers. In fact, most intermediary-based asset pricing models are founded on the limits-to-arbitrage paradigm (Shleifer and Vishny, 1997), which implies that the pricing kernel of households might not be relevant if some asset classes are too complicated for households to trade in directly. Presumably, derivatives contracts or OTC markets are too sophisticated to be directly accessed by most household investors. By contrast, sophisticated financial intermediaries play a central and dominant role in the market for derivatives and OTC assets (e.g., Siriwardane (2015)). Our paper provides supporting evidence that this distinction is important for understanding the behavior of a wide variety of assets. That our measure of financial distress performs significantly better on these exotic asset classes but relatively worse in US equities is consistent with the view that our measure better proxies for the financial distress of the relevant marginal intermediaries.[38]

4.2 Data source and measurement

Our measure of financial distress differs from AEM in both the definition of a financial intermediary and the data sources employed. We define intermediaries as the set of primary dealers and rely on market equity and book debt data for their publicly traded holding companies. AEM define intermediaries as the set of broker-dealer firms (often bank holding company subsidiaries) that feed into the Flow of Funds broker-dealer accounts, and use the book equity and debt data reported in those accounts.[39]

[37] In unreported results we also consider a three-factor horse-race specification that includes our capital ratio factor and the AEM leverage factor together (along with the market return). The capital ratio factor risk price results are broadly similar to those in our main specification.

[38] As mentioned, the alternative view that heterogeneous intermediaries specialize in different markets is consistent with the modest differences in risk prices that we estimate in some asset classes.

[39] Flow of Funds broker-dealer data are from SEC tabulation of regulatory filings. It includes most broker-dealer firms that file the Financial and Operational Combined Uniform Single (FOCUS) report or the Finances and Operations of Government Securities Brokers and Dealers (FOGS) report with their regulator (e.g. FINRA).

The two key differences are (i) our use of market values for constructing capital ratios, versus AEM's reliance on accounting book values, and (ii) our use of data at the holding company level, versus the broker-dealer subsidiary level information in the Flow of Funds. We explore the role of these differences below, and find that the latter difference is more likely to be the driving force.

4.2.1 Market leverage vs. book leverage

Our aim in constructing the capital ratio is to provide a current measure of financial distress that reflects the information available in prevailing market prices. Virtually all intermediary asset pricing theories would suggest using *market* values, which reflect forward looking information available in traded securities prices. [40] The inverse of our market equity capital ratio is referred to as "market leverage."

Book leverage, on the other hand, relies on accounting statement data for both equity and debt. One would expect a positive correlation between market and book capital ratios due to the fact that broker-dealers and banks are required to frequently mark their books to market. When mark-to-market is implemented perfectly, book leverage coincides with its market counterpart.[41] Because Flow of Funds data only includes book data for broker-dealers, Adrian et al. (2014a) rely on book leverage for their analysis, and appeal to mark-to-market accounting to support the timeliness and accuracy of their measure.[42]

An advantage of our data set is that we have access to both book and market equity values. We construct both book and market capital ratios for our sample of primary dealers, where the book capital ratio is defined as in (6), but replaces market equity with its corresponding book equity. We then investigate whether differences in the two measures can potentially reconcile the drastic

[40]While the market value of equity is readily available for publicly traded firms, market debt values are much more difficult to measure. Instead, we follow the standard approach in empirical corporate finance (e.g., (Leary and Roberts, 2005)) and use non-financial firms' most recently published book value of debt from accounting statements. As we argued in Section 3.1.1, this approximation is even more convincing in our context of financial firms, because the majority of bank holding companies' liabilities consist of safe short-term debt such as deposits, repurchase agreements (repo), and trading liabilities which are to a large extent collateralized.

[41]One caveat is that the market value of an financial intermediary not only reflects the market value of the financial assets on its balance sheet, but also includes the present value of its profits earned from future activities. Our view is that this future enterprise value also affects the intermediary's financial distress, and therefore will show up in its pricing kernel.

[42]In the accounting literature, there is some debate regarding accounting manipulations in the practice of mark-to-market and there are indications that mark-to-market accounting is especially inaccurate during financial crises when capital requirements and credit channels tighten (Heaton, Lucas, and McDonald, 2010; Milbradt, 2012). Ball, Jayaraman, and Shivakumar (2012) provide a skeptical assessment of mark-to-market accounting in a large sample of banks' trading securities.

difference between our paper and AEM. For example, a negative correlation between book and market leverage in our sample could help explain the conflicting risk prices estimated in our study versus AEM.[43]

We find, however, that the market capital ratio of primary dealers is in fact strongly *positively* associated with book capital ratio. Book and market capital ratios have a correlation of 50% in levels and 30% in innovations, indicating qualitatively similar behavior between them. This is illustrated in the time series plot of Figure 4b, and suggests that Compustat book leverage of primary dealers is in fact counter-cyclical. We present more direct evidence in appendix Table A.2, where we estimate the two-factor asset pricing model replacing the market capital ratio factor with its corresponding book capital ratio. The estimated prices of intermediary book capital risk remain largely positive (though become much less significant) across different asset classes, consistent with idea that the market equity of financial institutions reflects more accurate and timely information than their (accounting) book equity.

Outside the sample of primary dealers, we find that book and market capital ratio measures are also highly correlated for the wider universe of publicly traded broker-dealers (all public US firms with SIC 6211 or 6221, which includes some primary dealers). This group generally includes smaller broker-dealers that mainly focus on securities trading. Here we find a 75% correlation between market capital ratio and book capital ratio, again indicating reasonably accurate marking-to-market.

The conclusion from this analysis is that the difference between market-based and book-based measures of financial distress is unlikely to be responsible for the tension between our facts and those of AEM.

4.2.2 Holding company vs. broker-dealer subsidiary

The more likely discrepancy between AEM and our paper is that we measure financial distress at the holding company level for primary dealers, while the Flow of Funds data used by AEM only aggregates balance sheet information at the broker-dealer subsidiary level. Most NY Fed primary dealers are the broker-dealer subsidiaries of a large financial institutions holding companies.

[43] Previous literature such as Adrian et al. (2014b) and Adrian and Shin (2014) show that market and book leverage can be negatively correlated for banks, and therefore note that empirical analyses can be sensitive to choice of market-based versus book-based measures.

Flow of Funds data come from quarterly FOCUS and FOGS reports filed with the Securities and Exchange Commission (SEC) by these broker-dealer arms in isolation from other parts of their larger institutions. The underlying Flow of Funds data is therefore not publicly available. However, as most primary dealers are owned by publicly traded companies, market and financial statement data for the holding company is widely available, and form the basis of our analysis. In short, our definition of an intermediary is broader than AEM in the sense that we treat the entire holding company as the observation of interest.[44]

The holding companies of primary dealers often hold significant commercial banking businesses,[45] making the distinction between holding company and broker-dealer arm potentially important. We find that the AEM implied capital ratio (i.e., the inverse of AEM leverage) is more closely in line with the capital ratio of non-primary dealers (defined in Section 3.2.4) than that of primary dealers. While the AEM implied capital ratio and that of our primary dealer sample are strongly negatively correlated at -59%, the correlation between the AEM capital ratio and non-primary dealer capital ratio is 71 percentage points higher, at positive 12%. As shown in Table 2 and discussed in Section 3.2.4, the small overall size of non-primary dealers suggests that the broker-dealer business is the dominant segment in these firms. The large difference between the correlations of AEM with primary versus non-primary dealers is consistent with the interpretation that AEM only captures the leverage of broker-dealer sector, while the holding companies of primary dealers include other intermediary businesses with potentially different leverage patterns.

A key distinction between these two approaches—holding company data versus subsidiary-level broker-dealer data—rests on the role of internal capital markets in the primary dealer's holding company. A well established view in corporate finance is that internal capital markets within a conglomerate are likely to diversify and transmit adverse financial shocks across divisions (e.g. Stein, 1997; Scharfstein and Stein, 2000). If internal capital markets are important sources of funds for broker-dealer subsidiaries, then the capital ratio of the intermediary's holding company is the economically relevant measure of financial distress. In the banking literature, Houston, James, and Marcus (1997), Houston and James (1998), and de Haas and van Lelyveld (2010) present evidence

[44] At the same time, by focusing on primary dealers, we hone in on only the largest and most active intermediaries. By incorporating all broker-dealers that are subject to regulatory oversight, the Flow of Funds includes many small and standalone dealers.

[45] For instance, JP Morgan Securities LLC is the broker-dealer subsidiary of JP Morgan, and Citigroup Global Markets Inc. fulfills that role under the Citigroup umbrella.

to this effect. For instance, Houston et al. (1997) show that a bank subsidiary's loan growth more strongly correlates with the holding company's capital position than with the subsidiary's own capital position.

From a regulatory standpoint, both the holding company and many of its subsidiaries are subject to Basel-type capital and reserve requirements, but it is the publicly-traded holding company that raises outside equity, which it then allocates to its wholly-owned subsidiaries. Through this channel, the financial distress of a holding company's mortgage arm can be transmitted to its broker-dealer arm. Even if this broker-dealer arm is well-capitalized on its own, it is likely to experience pressure to transfer its excess capital to the loss-making mortgage arm. Conversely, a poorly-performing broker-dealer arm could benefit from the backing of a diversified and well-capatilized holding company that can easily raise outside equity.[46]

Two bankruptcy post-mortems provide rare opportunities to learn about the funding schemes that large financial intermediaries use in practice, which are otherwise hidden in publicly available consolidated reports. These glimpses into the internal capital markets of large financial institutions illustrate the fungibility of capital within broker-dealer holding companies both during normal times and when close to bankruptcy. The first is the 2008 bankruptcy of Lehman Brothers. The bankruptcy examiner describes Lehman Brothers Holdings as a "central banker" for Lehman subsidiaries (Valukas, 2010, Vol. 5, p. 1552, 1944). Each day excess cash was transferred from subsidiaries to the holding company and then used to cover the funding needs of subsidiaries with negative cash positions. In the days immediately prior to Lehman's bankruptcy filing on September 15, 2008, its broker-dealer units (the European unit in particular) required significant funding, and the holding company still used its liquid non-broker-dealer assets to guarantee the obligations of its broker-dealer subsidiaries to their clearing banks. This point is further corroborated by the bankruptcy case of the Drexel Burnham Lambert Group in 1990, which led to the liquidation of its

[46] The liquidity management section in JP Morgan's 2015 annual report (p. 159) states: "*The Parent Company acts as a source of funding to its subsidiaries. The Firm's liquidity management is intended to maintain liquidity at the Parent Company, in addition to funding and liquidity raised at the subsidiary operating level, at levels sufficient to fund the operations of the Parent Company and its subsidiaries for an extended period of time in a stress environment where access to normal funding sources is disrupted.*" And, large primary dealer holding companies continue to guarantee the obligations of their subsidiaries. The Goldman Sachs Group, Inc.'s 2015 annual report states that it has "*guaranteed the payment obligations of certain of its subsidiaries, including GS&Co., GS Bank USA and GSEC subject to certain exceptions. In addition, the Goldman Sachs Group Inc. guarantees many of the obligations of its other consolidated subsidiaries on a transaction-by-transaction basis, as negotiated with counterparties. These guarantees may require Group Inc. to provide substantial funds or assets to its subsidiaries or their creditors or counterparties at a time when Group Inc. is in need of liquidity to fund its own obligations.*"

broker-dealer affiliate. In the three weeks before it filed for bankruptcy, approximately $220 million was transferred to the holding company from its broker-dealer arm in the form of short-term loans. This instance of capital siphoning led the SEC to initiate group-wide risk assessments for all financial institutions with significant broker-dealer subsidiaries because, in practice, the ring-fencing of regulated subsidiaries is far from perfect.[47]

Of course, if internal capital markets within the holding company malfunction, then the financial distress of the primary dealer might be more directly reflected by the broker-dealer arm's own capital structure. The importance of internal capital markets within the bank holding company is ultimately an empirical question. Our evidence based on holding company financial ratios indirectly supports the view that internal markets are important to understanding the effect of intermediary distress on asset prices.

Besides internal capital markets, other mechanisms could also explain why aggregate holding company data provides a better proxy for financial distress of intermediaries, and it is beyond the scope of this paper to tell these stories apart. One might posit that the broker-dealer's funding ability in the short-term debt market is heavily influenced by the perceived risk of the entire holding company, which is proxied by its market capital ratio. Alternatively, He et al. (2010) and Hanson et al. (2015) argue that during economic downturns broker-dealers offload risky assets to commercial banks, which enjoy access to stable deposit funding. In this case, the balance-sheet adjustments could also occur through external capital markets transactions. Indeed, based on this idea, the next subsection fleshes out a theoretical framework to reconcile the difference between our paper and AEM, with economics similar to internal capital markets.

4.3 Differences in theoretical motivation

The interpretation of differences in our empirical results is complicated by the fact that different intermediary models predict different signs for the price of risk on intermediary capital shocks. In this subsection we discuss the theoretical distinction between two classes of intermediary asset pricing models, which we dub either "equity constraint" or "debt constraint" models.

The equity constraint framework originates with net worth-based based models such as Bernanke

[47]See testimony of Robert L.D. Colby before the U.S. House Subcommittee on Financial Institutions and Consumer Credit dated September 14, 2006, and Adoption of Amendments to SEC Rule 15c3-1 Regarding Withdrawals of Net Capital dated March 5, 1991.

and Gertler (1989) and Holmstrom and Tirole (1997), and is exemplified by He and Krishnamurthy (2013, 2012) and Brunnermeier and Sannikov (2014). In these models, an adverse shock to the intermediary's equity capital reduces its risk bearing capacity. This leads to a fall in asset prices which directly increases the intermediary's leverage (holding debt fixed). At the same time, this rise in leverage is countervailed by the intermediary endogenously reducing its debt financing. In equilibrium, the fall in equity values outweighs the debt reduction, and equilibrium leverage rises (this is especially true when there is no debt constraint, as in He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014)). In other words, from the standpoint of the intermediary, leverage is counter-cyclical, rising in distress states where the intermediary values its wealth the most. This corresponds to a negative price of leverage risk, or a positive price of capital ratio risk.

Another group of models, exemplified by Brunnermeier and Pedersen (2009) and Adrian and Shin (2014), are set in a "debt constraint" framework.[48] These models rule out equity financing by assumption; instead, they focus on a time-varying debt (or leverage) constraint that affects equilibrium pricing. The models often feature a binding collateralized borrowing constraint, either motivated by a value-at-risk constraint as in Adrian and Shin (2014) or an endogenous hair-cut as in Brunnermeier and Pedersen (2009). Bad times correspond to a tightening of the debt constraint reflected as lower allowable leverage, and this triggers deleveraging (i.e., the forced reduction of debt financing is sufficiently strong that outweighs the fall in equity value) and fire-sales, during which assets are sold to some second-best user at a lower equilibrium price. This directly implies that leverage is pro-cyclical in these models, which corresponds to a positive price for leverage risk (or a negative price of capital ratio risk).

This classification of theories, while in some ways over-simplified, is meant to clearly delineate how different financial constraints can give rise to different equilibrium leverage patterns. More importantly, we believe that given the spectrum of complexities in real world financial intermediation that these models may be attempting to describe, it should not be surprising that different intermediary models have some opposing predictions. It is likely that intermediaries face both equity and debt constraints to varying degrees in different states of the world, leading to more nuanced and complex behavior than either class alone can generate.[49]

[48]Other related papers are Geanakoplos and Fostel (2008), Adrian and Boyarchenko (2012) and Moreira and Savov (forthcoming).

[49]For instance, Garleanu and Pederson (2011) build a dynamic stochastic general equilibrium model with margin

A related possibility is that these two model classes describe different intermediary sub-sectors that interact in financial markets. He et al. (2010) and Ang, Gorovyy, and van Inwegen (2011) describe one example that supports this view. During a downturn, when the marginal value of wealth is likely to be high for all investors, hedge funds (who are perhaps closer to the type of intermediary described by debt constraint models) sell their assets to commercial banks (who may be better described by equity constraint models), and so leverage of these two sectors moves in opposite directions. In the appendix we present a simplified static equilibrium model that combines features of Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2012) into an intermediary model with two sub-sectors. It illustrates how a debt-constrained "hedge fund" sector has procyclical leverage in equilibrium while leverage of the equity-constrained "bank" sector is countercyclical.

An interesting direction for future theory is to investigate different economic conditions under which debt or equity constraints are more likely to impact asset values, and to use this to guide construction of a more sophisticated pricing kernel that nests both mechanisms in a state-dependent manner. Ultimately, it is an empirical question whether our capital risk factor, the AEM leverage factor, or some combination of the two is the most useful representation of the pricing kernel.

5 Robustness

This section presents an array of robustness tests that support our main findings.

5.1 Pre-crisis and post-1990 subsamples

Table 12 presents the performance of our intermediary capital risk factor and the AEM leverage factor during the 1970Q1–2006Q4 sample, which excludes the dramatic fluctuations associated with the financial crisis. This test is designed to address the concern that average returns in some asset classes are unduly influenced by the crisis subsample. We find that pre-crisis prices of capital ratio risk are substantially smaller in three asset classes, US bonds, sovereign bonds, and commodities.

constraints, which correspond to a "debt constraint" in our language. However, the dynamic nature of that model implies that the margin/debt constraint does not bind in the normal state of world, and binds only after a sequence of sufficiently negative shocks. This occasionally binding constraint is similar to He and Krishnamurthy (2013, 2012). In Garleanu and Pederson (2011), because the deleveraging force is relatively weak in "normal" times when the constraint does not bind, there is no simple monotonic relationship between leverage and state of the world.

In the other four asset classes, the price of intermediary capital risk remains economically large. In the all portfolios case, the risk price estimate is 9% per quarter, identical to that in the full sample and highly significant.

We separately investigate the recent sample beginning in 1990 in Table 13. The capital risk price estimate remains positive in all asset classes and economically large in five of the seven asset classes (the exceptions are equities and US bonds). The all portfolios estimate remains positive and significant, both economically and statistically.

5.2 Monthly frequency

Our main analysis focuses on the quarterly frequency, corresponding to the frequency of balance sheet data going into our capital ratio measure. Similarly, AEM construct their leverage factor based on Flow of Funds accounting data and is only available at the quarterly frequency.

An advantage of using CRSP data is that we can update the capital ratio as new market equity data arrives each month. As a result, one can construct the monthly capital ratio for primary dealers by using the monthly market equity information from CRSP, together with the most recent quarterly book debt of their holding companies in Compustat. We repeat our cross section analysis at the monthly frequency.

Table 14 presents the results. The estimated price of intermediary capital risk remains positive for all asset classes. The magnitudes of estimates are now in monthly terms, and should therefore be multiplied by three in order to compare with our quarterly estimates in Table 5. The monthly price of capital risk is noticeably weaker for equities, US bonds, and commodities, but remains economically meaningful in the other four asset classes. In the all portfolios test, the risk price estimate is 3% per month and statistically significant.

Our use of the most recently reported quarterly debt ignores within-quarter variation in the debt taken by primary dealers. This approximation may hurt our model performance at the monthly frequency, if the time-series variation in book debt plays a role in driving the pricing power of our intermediary capital risk factor. From Table 9 in Section 3.2.6 we observe that book debt growth does possess some pricing power, which suggests a potential explanation for the weaker monthly performance of our intermediary capital risk factor.

5.3 Return predictability and non-linearity

A common prediction of dynamic intermediary asset pricing models is a non-linear or, more precisely, state-dependent association between the risk premium and the degree of financial sector distress. As a result, expected asset returns are time-varying in these models and are predictable based on lagged state variables that captures financial distress. We perform time-series predictive regressions in each asset class to evaluate this prediction.

Our framework requires additional structure to derive the time-varying risk premium, which is typically a non-linear function of the state variable. In a simplified version of He and Krishnamurthy (2012) that focuses on the risk of intermediary capital ratio, the risk price can be described as

$$\lambda_{\eta,t} = \gamma Var_t \left[\frac{d\eta_t}{\eta_t} \right] = \gamma \sigma^2_{\eta,t} \propto \left(\frac{1}{\eta_t} \right)^2 , \tag{11}$$

In words, the risk premium is linear in the squared reciprocal of the capital ratio of the intermediary sector.

Guided by (11), we regress the one-year holding period return on an equal weighted portfolio of assets within each class on the lagged inverse of the squared intermediary capital ratio:

$$R^k_{t+1\to t+4} - r^f_t = a_k + b_k \frac{1}{\eta^2_t} + u_{t+1\to t+4}. \tag{12}$$

The model predicts a positive b_k coefficient in Equation (11) because low intermediary capital ratio (high leverage) states are associated with low expected future returns. The model's prediction is generally supported by Table 15, which reports a significantly positive $\hat{b}_k$ for five of the seven asset classes at the 10% significance level, and in four classes is significant at the 5% significance level.

The dependent variable in the last column of Table 15 is the weighted average of individual asset class portfolio returns, with weights inversely proportional to the unconditional standard deviation of a portfolio's return. This weighting scheme accounts for the fact that volatilities differ markedly across asset classes, so prediction results for an equal-weighted average would be driven by a subset of the highest volatility portfolios. We find a positive one-year-ahead predictive coefficient in the all portfolios test with a t-statistic of 3.13.[50]

[50] Test statistics in Table 15 use Hodrick (1992) standard errors to adjust for the fact that annual returns are being forecast using overlapping quarterly observations.

For comparison, we also report predictive regression results for AEM, replaces $1/\eta_t^2$ with their broker-dealer leverage ratio. The predictive coefficients are negative (as AEM would predict) in six out of seven classes, and are significant in three classes at the 10% level.

5.4 Single factor models

Our main analysis focuses on a two-factor structure for the pricing kernel. Although the economic rationale to include the market return is standard, the empirical price of risk associated with the market return is generally insignificant in Table 5. Here we consider a one-factor specification that omits the market return.

Table 16 presents the estimation results. The only meaningful difference compared to our main results in Table 5 appears in the case of the 25 Fama-French portfolios, where the price of our intermediary capital risk is insignificant while the AEM result remains strong, and in the case of commodities where both are insignificant. This result is consistent with the fact that AEM has a larger t-stat (Table 10) than the t-stat for our intermediary capital risk (Table 5) for the equity market. But, for all other asset classes, the primary dealer capital ratio consistently carries a positive and significant risk price, while the AEM leverage risk price estimates take opposite signs in CDS, Options, and FX markets.

Thus, it turns out that especially for equities, it is important to include the market return when estimating the time-series betas on the capital risk factor, despite the fact that the price of market risk is statistically zero in the second-stage cross-sectional regression of Table 5. Our results are therefore consistent with compensation for financial sector risk that is orthogonal to general economic conditions.

5.5 Intermediary equity return

As explained in equation (4) in Section 2.2, the representative intermediary's pricing kernel only depends on its own net worth W_t^I, a result that holds exactly for log preferences (e.g., He and Krishnamurthy (2012)). A similar derivation to equation (3) implies that the return on the intermediary's equity should be a sufficient statistic for the intermediary pricing kernel with log preferences.

We test this single factor asset pricing model by constructing the value-weighted equity return for the primary dealer sector,[51] and report the estimated price of the primary dealers' equity return in Table 17. We find a significantly positive price for all asset classes other than the Fama-French 25 portfolios and commodities at the 10% level. For the all portfolios test, the estimated price is positive but not significant.

Recall that the single factor model with the factor being intermediary equity return holds only under log preferences. This is because the pricing kernel is the investor's marginal utility of consumption, and the consumption of log investors is always a constant fraction of their wealth. But if the representative intermediary has recursive preferences, then future market prospects (say persistent TFP shocks) will in general enter the intermediary's pricing kernel, suggesting a reduce-form specification in line with (2). Indeed, when we include the market return as another factor in panel (b) of Table 17, we recover estimates that are closely in line with our baseline results in Table 5. In particular, the estimated price of intermediary equity return factor is positive and significant throughout. Overall, the results in this table suggest that primary dealers' equity return plays a similar role as the capital risk factor, offering further evidence in support of intermediary asset pricing models.

5.6 Cross-sectional tests without an intercept

The empirical specification (8) allows the intercept γ_k, to vary across asset classes. The theory discussed in Section 3.2.2, however, predicts that $\gamma_k = 0$ for all k as in (9). This additional theoretical restriction might not be valid given potential model misspecification; however, it may matter for the empirical cross-asset pattern of estimated prices of intermediary capital risk λ_η^k.

In Table 18 we repeat our main cross-sectional regressions without an intercept. We find that constraining the intercept to zero has a minor impact on the prices of intermediary capital risk that we estimate and, if anything, their statistical significance improves.

5.7 Additional equity tests

Our tests span a wide range of asset classes, and are based on the hypothesis that primary dealers are active in all of them. However, the central reason we include equity in our earlier tests is to

[51] This value-weighted equity return is slightly different from the intermediary (market) equity growth rate constructed in Section 3.2.6. The latter "intermediary equity growth rate" includes new equity issuance, while the equity return does not.

remain comparable with recent empirical work in intermediary asset pricing. Relative to other asset classes that trade over-the-counter where primary dealers play a prominent role, these large banking-oriented financial institutions are not obviously active (and hence not necessarily marginal traders) in equity markets. Although holding positions do not necessarily reveal the nature of trading activities or whether an investor is marginal, they are nonetheless indicative: According to its annual report, Goldman Sachs held at the end of fiscal year 2011 about \$65 billion of equity securities. Meanwhile, their derivatives positions were \$96.7 trillion outstanding in gross and \$80 billion in net. This stunningly large gross number more accurately reflects the extent of their trading activity.[52]

In this subsection, we further explore the ability of intermediary capital risk to explain cross sectional differences in stock portfolio returns. First, we analyze the role that equity portfolios play in our multi-market estimates for the price of capital risk. The first column in Table 19 (labeled "All ex. FF25") reports the estimated pricing model for our "all portfolios" cross section but excluding equity portfolios. Our main conclusions are not driven by the inclusion of equity as the point estimate rises slightly when equity portfolios are omitted.

Next, we include 10 momentum-sorted portfolios (also from Ken French) along with the 25 size and value portfolios. We report estimates based on these 35 portfolios with a restricted zero intercept (second column) and with a free intercept parameter (third column). The fourth and fifth columns report "all portfolios" results including momentum in models with unrestricted and restricted intercepts. The equity-only estimate is positive and significant when the intercept is restricted to be zero, but the estimate drops to 0.12 when the intercept is a free parameter, indicating that our equity results are sensitive to the inclusion of momentum-sorted portfolios. The "all portfolios" estimate, however, remains large and statistically significant regardless of momentum's inclusion in test portfolios, and regardless of the intercept specification.

Lastly, in columns six through nine, we include 21 international (country-level) stock indices along with the 25 size and value portfolios for the US.[53] Including international equity indices

[52]Goldman Sachs's 2011 annual report states: "Notional amounts, which represent the sum of gross long and short derivative contracts, provide an indication of the volume of the firm's derivative activity; however, they do not represent anticipated losses." In contrast, Charles Schwab, a standalone broker-dealer who focuses on equity market, report no derivative trading activity on its 2011 annual report.

[53]Data are from Global Financial Data and include countries with return data available back to 1970. This includes Australia, Finland, Netherlands, Spain, Hong Kong, Japan, UK, Ireland, Italy, Austria, Belgium, South Korea, Greece, Portugal, Norway, Switzerland, Singapore, Israel, Denmark, Germany, and France. We do not expect

leads to the same qualitative conclusions as our earlier estimates. The capital risk price is positive and significant at the 10% level or better in the equity-only specification, in the "all portfolios" specification, and with or without a restricted intercept.

6 Conclusion

We find that differences in assets' exposure to innovations in the capital ratio of primary dealers explain variation in expected excess returns on equities, US bonds, foreign sovereign bonds, options, CDS, commodities, and currencies. Our intermediary capital risk factor carries a positive price of risk and is strongly pro-cyclical, implying counter-cyclical intermediary leverage. Our findings lend new empirical support to the view that financial intermediaries are marginal investors in many asset classes, and in turn support the view that the financial soundness of these intermediaries is important for understanding wide ranging asset price behavior.

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A Appendix

The purpose of this appendix is to offer a general equilibrium framework to reconcile the empirical regularities documented in Adrian et al. (2014a) and our paper. For simplicity the model will be cast in a one-period setting, although given the "myopic" objective of agents (risk neutral and log preferences) the analysis will be valid in a dynamic setting. We do not solve for equilibrium asset prices. Instead, we focus on the implications of general equilibrium leverage patterns for heterogeneous financial sectors, taking as given some well-known equilibrium properties of state-dependent asset pricing moments established in the literature. A version of this model was proposed in a conference discussion of our paper by Alexi Savov, to whom we are grateful for the suggestion.

The model combines the key features of He and Krishnamurthy (2012) and Brunnermeier and Pedersen (2009). There are three classes of agents. "Households" are assumed to only hold zero net supply riskless assets with an endogenous return of r^f, due to lack of sophistication or infinite risk-aversion. "Hedge funds" are risk-neutral but face a VaR constraint that binds in equilibrium, as in Adrian and Shin (2014). They are meant to represent the group of intermediaries (dealers and hedge funds) studied in Adrian et al. (2014a). "Banks" are risk-averse and have mean-variance preferences, with an absolute risk aversion of γ, following He and Krishnamurthy (2012), and correspond to the holding companies of primary dealers that our paper studies. Hedge funds and banks both actively trade in the risky asset market, which offers an endogenous return of R.

Of course, in practice holding companies are likely to include both proprietary trading and traditional banking businesses.[54] And, in our framework, the financial health of the commercial banking sector matters for the equilibrium pricing of sophisticated financial assets if internal capital markets in holding companies are well-functioning.

Denote aggregate wealth by W. The wealth (net worth) of the hedge fund sector is denoted by $W^{HF} \equiv w^{HF} W$, and the wealth of bankers by $W^B \equiv w^B W$. The lower case symbols w^{HF} and w^B indicate the wealth fraction of each sector relative to the whole economy. Both dealers and banks can take on leverage, so that their asset positions X^j may be greater than their net worth W^j, $j \in \{HF, B\}$. Denote the leverage choice as $\alpha^j \equiv \frac{X^j}{W^j}$ (assets over equity), and the resulting portfolio return by R^j_{t+1}. Then we have

$$\frac{W^j_{t+1}}{W^j_t} = R^j_{t+1} \equiv r^f_{t+1} + \alpha_i \left(R_{t+1} - r^f_{t+1}\right),\ j \in \{HF, B\}. \tag{A.1}$$

In our model, hedge funds solve

$$\max_{\alpha_{HF}} \mathbb{E}_t \left[W^{HF}_{t+1}\right] \ s.t.\ Var_t\left(R^{HF}_{t+1}\right) = \alpha^2_{HF}\sigma^2_{R,t} \le \overline{\sigma}^2, \tag{A.2}$$

where $\sigma^2_{R,t} \equiv Var_t\left(R_{t+1}\right)$ is the conditional volatility of the risky asset and $\overline{\sigma}^2$ is the maximum allowable risk in the hedge fund's position. Assuming that $\mathbb{E}_t\left(R_{t+1} - r^f_{t+1}\right) > 0$ so that the risky asset offers a strictly positive risk premium in equilibrium, the solution to (A.2) is $\alpha_{HF} = \frac{\overline{\sigma}}{\sigma_{R,t}}$. On the other hand, given (A.1) bankers solve problem

$$\max_{\alpha_B} \mathbb{E}_t\left[W^B_{t+1}\right] - \frac{\gamma}{2} Var_t\left(W^B_{t+1}\right),$$

whose solution is

$$\alpha_B = \frac{1}{\gamma}\frac{\mathbb{E}_t\left(R_{t+1} - r^f_{t+1}\right)}{\sigma^2_{R,t}}.$$

Finally, we have the market clearing condition. Because only hedge funds and banks can hold risky assets, we have

$$w^B \alpha_B + w^{HF}\alpha_{HF} = 1. \tag{A.3}$$

We first explain how our model is able to generate leverage patterns found in the data. The solution for α_{HF} shows that hedge funds have lower leverage in bad states, when $\sigma_{R,t}$ tends to be high (He and Krishnamurthy (2012), Brunnermeier and Pedersen (2009)). That is, hedge funds have procyclical leverage. Also, because both hedge funds and banks take on leverage (and households save) in equilibrium, it is easy to show that their wealth shares w_B and w_{HF} go down following negative fundamental shocks.[55] Combining the two results above, (A.3) implies that $\alpha_B = \frac{1 - w^D \alpha_D}{w_B}$ increases in bad states, so banks have countercyclical leverage in equilibrium. Intuitively, this

[54] The latter is more likely to face equity-based constraints. Given deposit guarantees, the US commercial banking system is able to attract demand deposits even during severe crises like that in 2008.

[55] Take banks as an example. Leverage implies that $\frac{dW^B}{W^B} < \frac{dW}{W}$ following a negative shock. I.e., banks experience a worse equity return than the aggregate market. But $\frac{dW^B}{W^B} < \frac{dW}{W}$ is equivalent to $dw^B = d\left(\frac{W^B}{W}\right) < 0$.

correponds to the situation in which hedge funds sell their assets to commercial banks after negative shocks, and the leverages of these two sectors move in the opposite directions. This pattern is empirically supported by He et al. (2010) and Ang et al. (2011).

We briefly discuss how we map the pricing kernel in this simple model to the one used in our paper. In this simple model banks are always marginal in pricing any asset. Given their mean variance preferences, the "CAPM" type of result holds if one use the banks' equity return as the pricing kernel, similar to He and Krishnamurthy (2012). Naturally, the leverage of hedge funds can also be used to represent the pricing kernel, as in Adrian et al. (2014a), because hedge fund leverage α_D perfectly (negatively) correlates with bank equity.

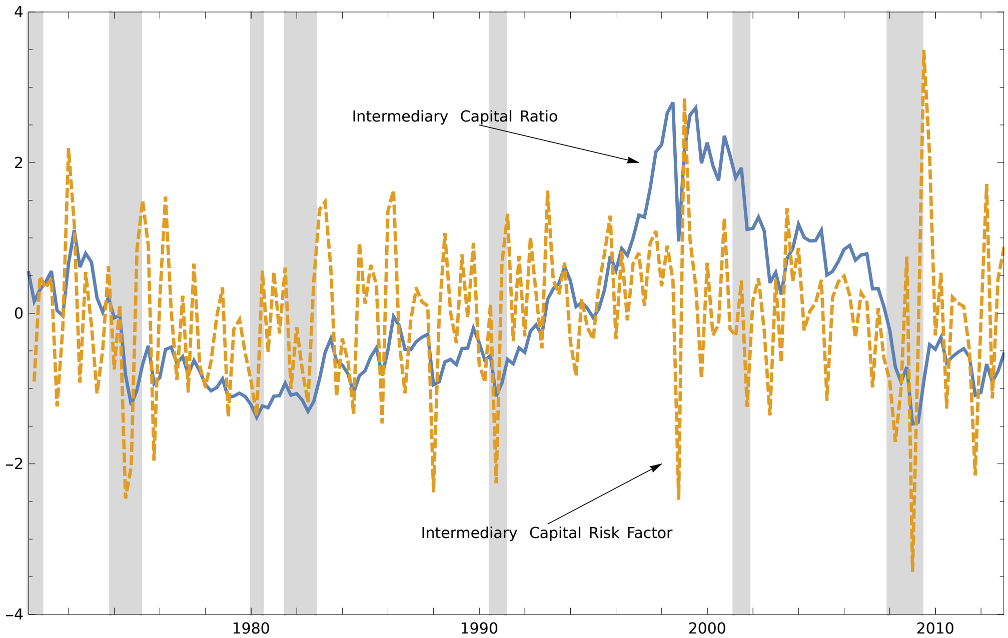


Figure 1: **Intermediary Capital Ratio and Risk Factor**
Intermediary capital risk factor (dashed line) is AR(1) innovations to the market-based capital ratio of primary dealers (solid line), scaled by the lagged capital ratio. Both time-series are standardized to zero mean and unit variance for illustration. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shaded regions indicate NBER recessions.

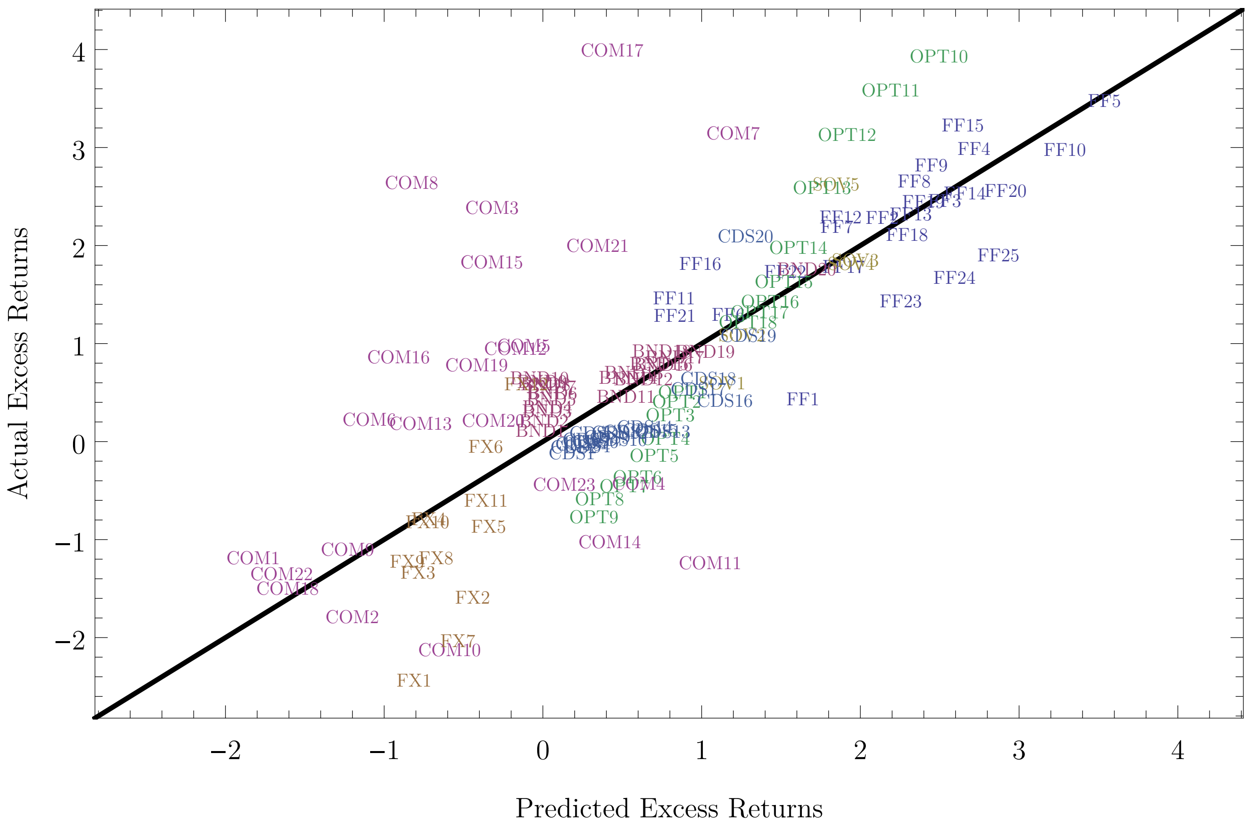


Figure 2: **Pricing Errors: All Portfolios**

Actual average percent excess returns on all tested portfolios versus predicted expected returns using their risk exposures (betas) with respect to shocks to the intermediary capital ratio and the excess return on the market. Test portfolios are abbreviated based on their asset class: equities (FF), US bonds (BND), foreign sovereign bonds (SOV), options (OPT), CDS, commodities (COM), and foreign exchange (FX). Distance from the 45 degree line represents pricing errors (alphas). Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio.

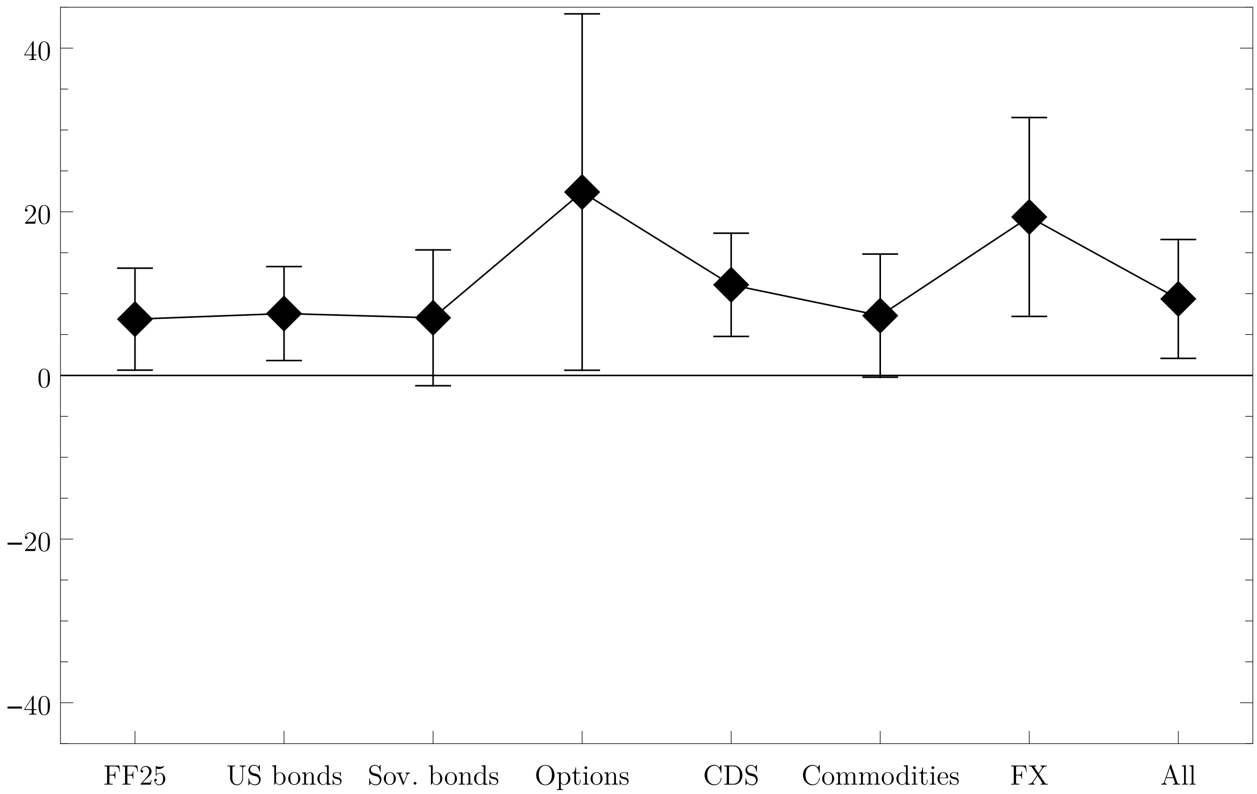
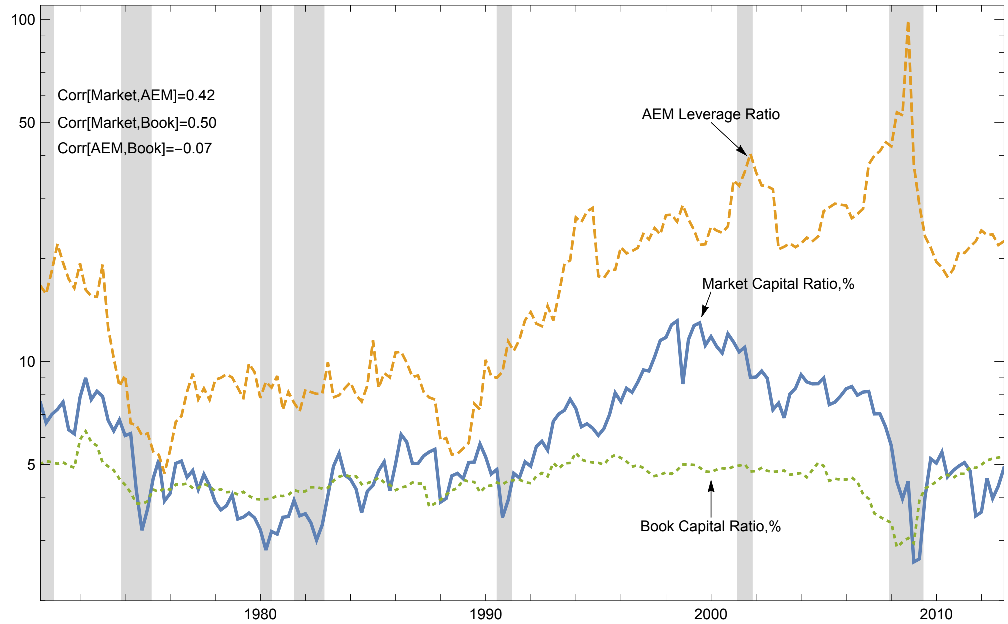
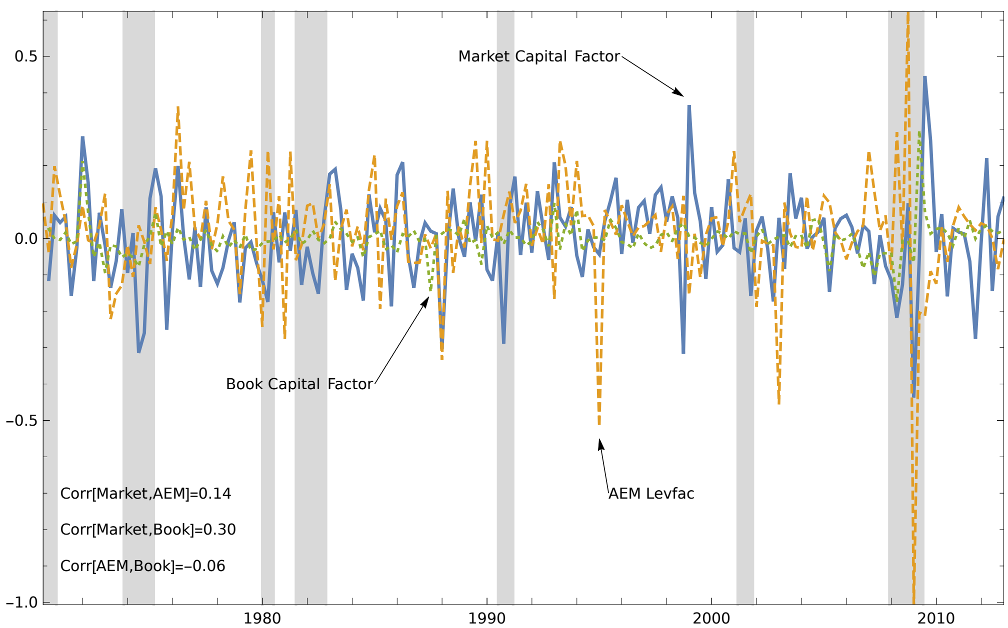


Figure 3: **Intermediary Capital Risk Price λ_η Estimates by Asset Class**
Risk price estimates for shocks to the intermediary capital ratio, from a two-factor model that includes the excess return on the market. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Error bars are the 95% confidence interval around the point estimates, calculated using GMM standard errors that adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.



(a) **Capital and Leverage Ratios (Levels)**



(b) **Risk Factors (Innovations)**

Figure 4: **Intermediary Capital Measures Comparison**
Sub-Figure (a) compares our main state variable of interest, the aggregate market-based capital ratio of NY Fed primary dealers with other measures of intermediary capital. Market capital ratio at t is defined as $\frac{\Sigma_i marketequity_{it}}{\Sigma_i(marketequity_{it}+bookdebt_{it})}$, where market equity is outstanding shares multiplying stock price, and book debt is total asset minus common equity $AT - CEQ$. Book capital ratio simply replaces $marketequity_t$ with $bookequity_t$ in this calculation. AEM leverage ratio is the leverage ratio of the broker-dealer sector used by Adrian et al. (2014a), constructed from Federal Reserve Z.1 security brokers and dealers series: Total Financial Assets (FL664090005) divided by Total Financial Assets (FL664090005) less Total Liabilities (FL664190005). In Sub-Figure (a), the capital ratios are in the scale of percentage points (i.e., 5 means 5%). Sub-Figure (b) draws a similar comparison for the risk factors (innovations in the state variables). Our main asset pricing factor is AR(1) innovations to the market-based capital ratio of primary dealers, scaled by the lagged capital ratio. The quarterly sample is 1970Q1–2012Q4. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Shaded regions indicate NBER recessions.

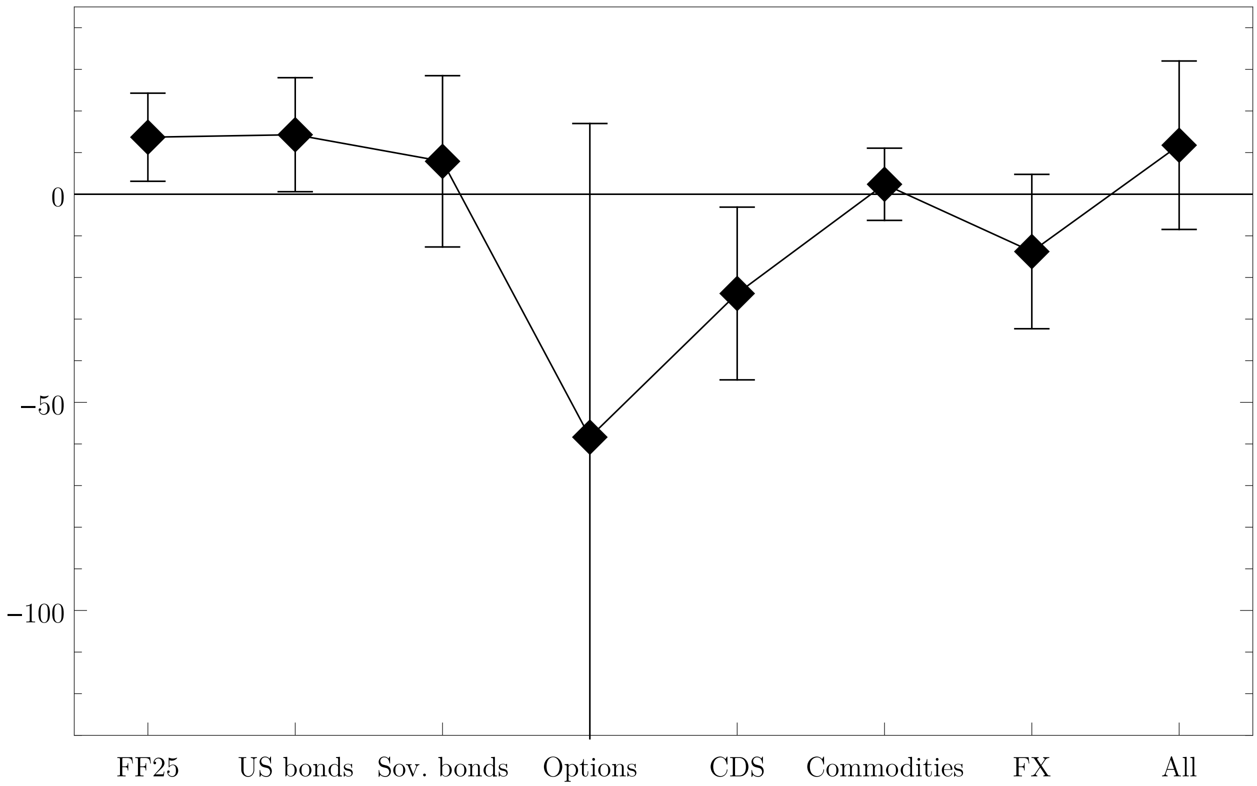


Figure 5: **AEM Leverage Factor Risk Price Estimates by Asset Class**

Risk price estimates for shocks to the Adrian et al. (2014a) leverage factor (AEM), from a two-factor model that includes the excess return on the market. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Error bars are the 95% confidence interval around the point estimates, calculated using GMM standard errors that adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

Primary Dealer	Holding Company	Start Date
Goldman, Sachs & Co.	Goldman Sachs Group, Inc., The	12/4/1974
Barclays Capital Inc.	Barclays PLC	4/1/1998
HSBC Securities (USA) Inc.	HSBC Holdings PLC	6/1/1999
BNP Paribas Securities Corp.	BNP Paribas	9/15/2000
Deutsche Bank Securities Inc.	Deutsche Bank AG	3/30/2002
Mizuho Securities USA Inc.	Mizuho Financial Group, Inc.	4/1/2002
Citigroup Global Markets Inc.	Citigroup Inc.	4/7/2003
UBS Securities LLC	UBS AG	6/9/2003
Credit Suisse Securities (USA) LLC	Credit Suisse Group AG	1/16/2006
Cantor Fitzgerald & Co.	Cantor Fitzgerald & Company	8/1/2006
RBS Securities Inc.	Royal Bank Of Scotland Group PLC, The	4/1/2009
Nomura Securities International,Inc	Nomura Holdings, Inc.	7/27/2009
Daiwa Capital Markets America Inc.	Daiwa Securities Group Inc. (Japan)	4/1/2010
J.P. Morgan Securities LLC	JPMorgan Chase & Co.	9/1/2010
Merrill Lynch, Pierce, Fenner & Smith	Bank Of America Corporation	11/1/2010
RBC Capital Markets, LLC	Royal Bank Holding Inc.	11/1/2010
SG Americas Securities, LLC	Societe Generale	2/2/2011
Morgan Stanley & Co. LLC	Morgan Stanley	5/31/2011
Bank Of Nova Scotia, NY Agency	Bank Of Nova Scotia, The	10/4/2011
BMO Capital Markets Corp.	Bank Of Montreal	10/4/2011
Jefferies LLC	Jefferies LLC	3/1/2013
TD Securities (USA) LLC	Toronto-dominion Bank, The	2/11/2014

Table 1: **Primary Dealers as of February 11, 2014**
Primary dealers, as designated by the NY Fed serve as its trading counterparties as it implements monetary policy. Primary dealers are obliged to: (i) participate consistently in open market operations to carry out US monetary policy; and (ii) provide the NY Fed's trading desk with market information and analysis. Primary dealers are also required to participate in all US government debt auctions and to make reasonable markets for the NY Fed. From 1960 to 2014 a total of 168 dealers were designated as primary ones, some of whom lost this designation previously. See http://www.newyorkfed.org/markets/primarydealers.html for current and historical lists of primary dealers.

	Total Assets			Book Debt			Book Equity			Market Equity		
	BD	Banks	Cmpust.	BD	Banks	Cmpust.	BD	Banks	Cmpust.	BD	Banks	Cmpust.
1960-2012	0.959	0.596	0.240	0.960	0.602	0.280	0.939	0.514	0.079	0.911	0.435	0.026
1960-1990	0.997	0.635	0.266	0.998	0.639	0.305	0.988	0.568	0.095	0.961	0.447	0.015
1990-2012	0.914	0.543	0.202	0.916	0.550	0.240	0.883	0.444	0.058	0.848	0.419	0.039

Table 2: **Primary Dealers as Representative Financial Intermediaries**

Average sizes of prime dealers relative to all broker-dealers (BD), all banks (Banks), and all firms in Compustat (Cmptust). At the end of each month, we calculate the total assets (and book debt, book equity, and market equity) of prime dealers and divide them by the total for the comparison group. To make the samples comparable, we focus in this table only on US-based primary dealer holding companies that are in the CRSP-Compustat data. We report the time series average of this ratio in each sample period.

	Market Capital	Book Capital	AEM Leverage
Market Capital	1.00	0.50	0.42
Book Capital		1.00	-0.07
AEM Leverage			1.00
E/P	-0.83	-0.38	-0.64
Unemployment	-0.63	-0.10	-0.33
GDP	0.18	0.32	-0.23
Financial Conditions	-0.48	-0.53	-0.19
Market Volatility	-0.06	-0.31	0.33

(a) Correlations of Levels

	Market Capital Factor	Book Capital Factor	AEM Leverage Factor
Market Capital Factor	1.00	0.30	0.14
Book Capital Factor		1.00	-0.06
AEM Leverage Factor			1.00
Market Excess Return	0.78	0.10	0.15
E/P Growth	-0.75	-0.10	-0.18
Unemployment Growth	-0.05	0.12	-0.08
GDP Growth	0.20	0.09	0.04
Financial Conditions Growth	-0.38	-0.29	-0.06
Market Volatility Growth	-0.49	-0.18	-0.08

(b) Correlations of Factors

Table 3: **Pair-wise Correlations**

Time-series pair-wise correlations over the 1970Q1–2012Q4 sample. Market Capital (ratio) is defined as the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies, constructed using CRSP-Compustat and Datastream data. Market equity is outstanding shares multiplying stock price, and book debt is total asset minus common equity $AT - CEQ$. Market Capital Factor is our main asset pricing factor defined as AR(1) innovations to the market capital ratio, scaled by the lagged capital ratio. Book Capital and Book Capital Factor are similarly defined, but uses book equity instead of market equity. The AEM implied capital is the inverse of broker-dealer book leverage from Flow of Funds used in AEM, and the AEM leverage factor ($LevFac$) is defined as the seasonally adjusted growth rate in broker-dealer book leverage from Flow of Funds. Correlation for factors are with value-weighted stock market excess return, growth (log change) of the earnings-to-price ratio, Unemployment, GDP, the Chicago Fed National Financial Conditions Index (high level means poor financial conditions), or realized volatility of CRSP value-weighted stock index.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Mean($\mu_i - r_f$)	2.18	0.72	1.97	1.11	0.28	0.37	-1.01	0.82
Std($\mu_i - r_f$)	0.70	0.39	1.13	1.47	0.52	1.70	0.82	1.40
Mean($\beta_{i,\eta}$)	0.07	0.03	0.22	-0.01	0.06	-0.09	-0.08	0.01
Std($\beta_{i,\eta}$)	0.11	0.04	0.14	0.05	0.04	0.10	0.03	0.11
Mean($\beta_{i,W}$)	1.02	0.06	0.09	0.83	0.04	0.27	0.15	0.41
Std($\beta_{i,W}$)	0.30	0.07	0.12	0.11	0.03	0.26	0.04	0.44
Mean(R^2)	0.78	0.09	0.30	0.79	0.63	0.04	0.04	0.42
$p(\chi^2(\beta = 0))$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table 4: **Expected Returns and Risk Exposure by Asset Class**

Average percent excess returns $\mu_i - r_f$, and risk exposures (betas) to shocks to the intermediary capital ratio, denoted by $\beta_{i,\eta}$, and to the excess return on the market ($\beta_{i,W}$), across portfolios in each asset class. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. Betas are estimated in a first-stage time-series regression. Mean(x) and Std(x) denote respectively the mean and standard deviation of x across portfolios. $p(\chi^2(\beta = 0))$ is the p-value of a χ^2 statistic testing the hypothesis that the time-series betas are jointly zero: $T\beta' \left[Avar\left(\beta\right)\right]^{-1} \beta \to \chi^2\left(2N\right)$, where T is the number of quarters, N is the number of test assets, β is a $2N$ vector of betas, and $Avar\left(\beta\right)$ is its asymptotic covariance matrix implied by GMM.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	6.88	7.56	7.04	22.41	11.08	7.31	19.37	9.35
	(2.16)	(2.58)	(1.66)	(2.02)	(3.44)	(1.90)	(3.12)	(2.52)
Market	1.19	1.42	1.24	2.82	1.11	-0.55	10.14	1.49
	(0.78)	(0.82)	(0.32)	(0.67)	(0.41)	(-0.25)	(2.17)	(0.80)
Intercept	0.48	0.41	0.34	-1.11	-0.39	1.15	-0.94	-0.00
	(0.36)	(1.44)	(0.33)	(-0.31)	(-2.77)	(0.83)	(-0.83)	(-0.00)
R^2	0.53	0.84	0.81	0.99	0.67	0.25	0.53	0.71
MAPE, %	0.34	0.13	0.32	0.14	0.18	1.15	0.44	0.63
MAPE-R, %	0.40	0.26	0.45	0.68	0.39	1.40	0.62	0.63
RRA	2.71	3.09	2.52	8.90	3.61	2.88	8.26	3.69
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table 5: **Cross-sectional Asset Pricing Tests by Asset Class**

Risk price estimates for shocks to the intermediary capital ratio and the excess return on the market. The capital ratio is defined as the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

Benchmark:	CAPM	FF3F	FF5F	Momentum	PS-liquidity	LMW
Capital	9.35	9.14	8.81	9.69	7.87	7.56
	(2.52)	(1.98)	(2.46)	(2.84)	(1.75)	(1.76)
Market	1.49	1.62	1.33	1.54	1.21	
	(0.80)	(0.90)	(0.74)	(0.81)	(0.69)	
SMB		0.39	0.59			
		(0.42)	(0.68)			
HML		2.23	2.01			
		(1.36)	(1.46)			
CMA			-0.33			
			(-0.09)			
RMW			0.08			
			(0.04)			
MOM				-1.20		
				(-0.14)		
PS^{nt}					5.71	
					(0.64)	
LMW^{-}						0.77
						(0.58)
LMW						0.63
						(0.31)
Adj. R^2	0.71	0.80	0.69	0.73	0.67	0.70
MAPE, %	0.63	0.65	0.62	0.61	0.59	0.63
RRA	3.69	3.32	3.50	3.74	2.61	2.58
Assets	124	124	124	124	124	124
Quarters	172	172	172	172	172	172
Adj. R^2 w/o Capital	0.32	0.65	0.65	0.27	0.67	0.50
MAPE w/o Capital	0.85	0.86	0.82	0.85	0.83	0.87

Table 6: **Comparison with Commonly-used Pricing Factors**

Risk price estimates for shocks to the intermediary capital ratio and the excess return on the market, controlling for commonly used benchmark pricing factors. All test portfolios are included in all columns. The capital ratio is defined as the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. The Fama and French factors Small Minus Big (SMB), High Minus Low (HML), Conservative Minus Aggressive (CMA), Robust Minus Weak (RMW), and the momentum factor (MOM) are from Ken French's website. The non-traded Pástor and Stambaugh liquidity factor (PS^{nt}) is from L'uboš Pástor's website. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. Risk prices on the Lettau, Maggiori, and Weber downside risk (LMW^{-}) and normal times (LMW) factors are estimated as in the original paper. The quarterly sample is 1970Q1–2012Q4. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas. The bottom two statistics are adjusted R^2 and MAPE for similar specifications but without the intermediary capital risk factor.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	16.25	12.37	43.26	-85.93	66.77	-10.20	-2.61	11.03
	(2.45)	(0.69)	(1.24)	(-2.33)	(2.55)	(-1.52)	(-0.12)	(1.04)
Market	-2.45	3.82	5.56	-6.53	6.86	-0.87	11.76	1.40
	(-1.66)	(2.51)	(1.74)	(-1.20)	(2.99)	(-0.49)	(2.45)	(0.80)
Intercept	4.40	0.38	0.26	7.22	-0.41	-0.38	-2.14	0.25
	(3.36)	(1.49)	(0.22)	(1.48)	(-2.72)	(-0.62)	(-2.14)	(0.95)
R^2	0.54	0.82	0.81	0.97	0.86	0.11	0.50	0.46
MAPE, %	0.36	0.14	0.32	0.23	0.15	1.30	0.45	0.90
MAPE-R, %	0.62	0.30	1.29	1.33	0.34	1.67	1.06	0.90
RRA	1.94	1.49	3.95	-10.95	5.16	-1.33	-0.34	1.32
Assets	25	20	6	18	20	23	12	124
Quarters	165	148	65	103	47	105	135	172

(a) **Non-Primary Broker-Dealers**

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	-1.02	2.87	1.50	4.19	0.26	-0.38	6.87	0.32
	(-0.70)	(2.90)	(1.42)	(2.01)	(0.15)	(-0.45)	(2.16)	(0.45)
Market	-1.03	2.77	2.42	9.30	8.78	-0.91	14.30	1.73
	(-0.83)	(1.72)	(0.88)	(3.09)	(1.78)	(-0.52)	(2.78)	(1.04)
Intercept	3.31	0.38	1.56	-6.33	-0.21	0.53	-1.85	0.11
	(3.09)	(1.08)	(1.57)	(-2.99)	(-1.38)	(0.87)	(-1.55)	(0.20)
R^2	0.08	0.85	0.74	0.91	0.90	0.01	0.51	0.37
MAPE, %	0.54	0.12	0.46	0.38	0.13	1.40	0.46	0.84
MAPE-R, %	0.66	0.39	1.09	1.12	0.25	1.47	1.23	0.84
RRA	-1.57	5.78	3.35	9.16	0.53	-0.85	15.00	0.49
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

(b) **Non-Banks**

Table 7: **Primary Dealers are Special: a Placebo Test**

Risk price estimates for shocks to the capital ratios of complementary sets of financial intermediaries, and the excess return on the market. Panel (a) examines non-primary dealers defined as US firms in the broker-dealer SIC groups (6211, 6221) that are not in the NY Fed primary dealer list. Panel (b) examines non-banks defined as US firms with an SIC code that does not start with 6. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	5.97	2.05	10.01	24.37	14.04	8.78	13.63	10.67
	(2.09)	(0.48)	(0.91)	(2.33)	(3.17)	(1.73)	(1.61)	(2.70)
Market	0.16	4.20	-1.15	0.87	-0.79	-0.88	13.35	1.05
	(0.12)	(2.31)	(-0.11)	(0.25)	(-0.23)	(-0.43)	(2.96)	(0.63)
Intercept	1.47	0.34	0.40	0.77	-0.44	1.06	-1.93	0.19
	(1.29)	(2.55)	(0.32)	(0.27)	(-2.75)	(0.99)	(-1.66)	(0.26)
R^2	0.57	0.82	0.76	0.99	0.69	0.45	0.49	0.70
MAPE, %	0.33	0.13	0.39	0.12	0.18	1.05	0.45	0.63
MAPE-R, %	0.42	0.29	0.56	0.63	0.58	1.16	0.72	0.63
RRA	1.94	0.68	3.16	7.93	3.77	2.79	4.85	3.47
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table 8: **Equal-weighted Capital Ratio Risk Factor**

Risk price estimates for shocks to the equal-weighted average intermediary capital ratio and the excess return on the market. The equal-weighted average capital ratio is defined as the mean ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
ME	7.22	4.72	5.03	13.77	5.56	8.72	19.13	9.71
	(1.62)	(1.34)	(0.86)	(1.54)	(1.32)	(1.56)	(4.30)	(2.35)
BD	-2.00	4.09	-6.89	-5.85	-10.19	2.06	-0.18	-0.26
	(-1.51)	(1.53)	(-2.24)	(-0.93)	(-2.12)	(1.14)	(-0.08)	(-0.07)
Market	0.76	4.54	1.85	0.91	-0.52	0.00	8.62	1.68
	(0.46)	(2.01)	(0.48)	(0.19)	(-0.17)	(0.00)	(2.12)	(0.93)
Intercept	0.85	0.22	-0.19	-0.06	-0.42	0.43	-0.79	-0.18
	(0.56)	(1.19)	(-0.12)	(-0.02)	(-3.25)	(0.38)	(-0.76)	(-0.40)
R^2	0.51	0.89	0.90	0.99	0.86	0.28	0.54	0.77
MAPE, %	0.35	0.09	0.29	0.12	0.15	1.21	0.44	0.64
MAPE-R, %	0.44	0.41	0.47	0.68	0.22	1.53	0.52	0.64
RRA	2.39	1.55	1.38	4.20	1.50	2.65	6.57	3.21
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table 9: **Both Market Equity and Book Debt are Important for Pricing**
Risk price estimates for the market equity growth (ME) and book debt growth (BD) of the aggregate intermediary sector, and the excess return on the market. Both growth (log change) measures rely only on firms that are in the sample in both periods. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
AEM	13.70	14.30	7.90	-58.37	-23.85	2.39	-13.77	11.77
	(2.54)	(2.05)	(0.75)	(-1.52)	(-2.25)	(0.54)	(-1.46)	(1.14)
Market	0.89	4.05	3.17	1.73	4.55	-0.48	8.86	1.73
	(0.57)	(1.77)	(1.00)	(0.22)	(2.24)	(-0.31)	(2.62)	(0.91)
Intercept	0.79	0.26	1.03	-1.96	-0.12	0.43	-1.86	-0.07
	(0.56)	(0.64)	(1.65)	(-0.29)	(-1.15)	(0.66)	(-2.22)	(-0.05)
R^2	0.70	0.87	0.73	0.98	0.93	0.03	0.59	0.48
MAPE, %	0.27	0.12	0.45	0.16	0.11	1.40	0.36	0.81
MAPE-R, %	0.30	0.49	1.64	1.16	0.26	1.53	1.05	0.81
RRA	5.40	5.26	2.28	-18.78	-5.17	0.79	-4.91	4.64
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table 10: **Cross-sectional Asset Pricing Tests by Asset Class: AEM Leverage Factor**
Risk price estimates for the Adrian et al. (2014a) leverage factor (AEM) and the excess return on the market. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Mean($\mu_i - r_f$)	2.18	0.72	1.97	1.11	0.28	0.37	-1.01	0.82
Std($\mu_i - r_f$)	0.70	0.39	1.13	1.47	0.52	1.70	0.82	1.40
Mean($\beta_{i,AEM}$)	0.03	0.01	-0.01	-0.03	0.00	0.01	-0.02	0.00
Std($\beta_{i,AEM}$)	0.05	0.01	0.04	0.02	0.01	0.10	0.02	0.05
Mean($\beta_{i,W}$)	1.09	0.09	0.34	0.83	0.11	0.18	0.06	0.43
Std($\beta_{i,W}$)	0.20	0.10	0.22	0.17	0.07	0.22	0.05	0.45
Mean(R^2)	0.78	0.09	0.23	0.79	0.52	0.04	0.02	0.39
$p(\chi^2(\beta = 0))$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table 11: **Expected Returns and Risk Exposure by Asset Class: AEM Leverage Factor**

Average percent excess returns $\mu_i - r_f$, and risk exposures (betas) to the Adrian et al. (2014a) leverage factor (AEM) and to the excess return on the market ($\beta_{i,W}$), across portfolios in each asset class. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Betas are estimated in a first-stage time-series regression. Mean(x) and Std(x) denote respectively the mean and standard deviation of x across portfolios. $p(\chi^2(\beta = 0))$ is the p-value of a χ^2 statistic testing the hypothesis that the time-series betas are jointly zero: $T\beta' \left[Avar\left(\beta\right)\right]^{-1} \beta \to \chi^2\left(2N\right)$, where T is the number of quarters, N is the number of test assets, β is a $2N$ vector of betas, and $Avar\left(\beta\right)$ is its asymptotic covariance matrix implied by GMM.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	12.32	14.14	1.57	2.00	-0.16	-3.02	19.81	-33.61
	(1.84)	(2.22)	(0.33)	(0.31)	(-0.05)	(-0.56)	(2.04)	(-3.10)
Market	2.99	1.39	4.52	3.85	6.67	4.96	-0.15	5.29
	(1.14)	(0.72)	(2.56)	(2.79)	(2.54)	(2.05)	(-0.02)	(1.04)
Intercept	-1.47	0.32	0.29	0.19	1.72	0.52	1.27	-4.00
	(-0.59)	(0.18)	(2.11)	(3.56)	(1.98)	(0.80)	(0.22)	(-1.08)
R^2	0.70	0.72	0.86	0.83	0.71	0.54	0.99	0.98
MAPE, %	0.34	0.30	0.11	0.10	0.53	0.67	0.14	0.18
MAPE-R, %	0.41	0.46	0.23	0.26	0.89	2.10	0.81	1.40
RRA	7.25	8.32	0.92	1.18	-0.19	-3.48	12.02	-20.40
Assets	25	25	20	20	6	6	18	18
Quarters	148	148	128	128	48	48	83	83
	CDS		**Commod.**		**FX**		**All**	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	8.13	-15.84	-4.44	-1.22	16.32	-2.80	7.20	8.82
	(1.88)	(-2.50)	(-1.24)	(-0.51)	(2.82)	(-0.34)	(3.04)	(2.31)
Market	7.33	6.03	-1.88	-2.51	10.15	11.12	1.71	1.81
	(3.23)	(1.50)	(-1.10)	(-1.40)	(1.98)	(2.94)	(0.82)	(0.89)
Intercept	-0.13	-0.09	0.21	0.32	-0.59	-1.48	-0.04	-0.13
	(-1.55)	(-0.88)	(0.34)	(0.64)	(-0.55)	(-1.78)	(-0.08)	(-0.29)
R^2	0.84	0.95	0.23	0.19	0.55	0.52	0.64	0.53
MAPE, %	0.12	0.08	1.37	1.46	0.38	0.41	0.72	0.94
MAPE-R, %	0.16	0.48	1.95	1.81	0.58	0.96	0.72	0.94
RRA	5.48	-10.68	-2.68	-0.73	10.14	-1.74	4.24	5.19
Assets	20	20	23	23	12	12	124	124
Quarters	23	23	81	81	123	123	148	148

Table 12: **Cross-sectional Asset Pricing Tests by Asset Class: Pre-crisis Sample**
Risk price estimates for shocks to the intermediary capital ratio (HKM) or the Adrian et al. (2014a) leverage factor (AEM), and the excess return on the market. Here we focus on the pre-crisis quarterly sample 1970Q1–2006Q4. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	2.24	8.80	3.96	0.33	7.25	7.90	36.22	-51.87
	(0.75)	(1.34)	(1.21)	(0.05)	(1.58)	(0.75)	(1.21)	(-1.95)
Market	-0.06	0.19	2.88	3.04	1.29	3.17	-0.19	2.17
	(-0.03)	(0.11)	(2.01)	(2.07)	(0.33)	(1.00)	(-0.03)	(0.35)
Intercept	2.05	1.92	0.74	0.73	0.34	1.03	1.28	-2.05
	(1.40)	(1.37)	(4.60)	(4.42)	(0.32)	(1.65)	(0.21)	(-0.34)
R^2	0.28	0.30	0.64	0.64	0.80	0.73	0.96	0.95
MAPE, %	0.42	0.41	0.22	0.22	0.33	0.45	0.22	0.26
MAPE-R, %	0.54	0.67	0.48	0.67	0.36	1.34	0.92	1.17
RRA	0.74	2.90	1.25	0.10	2.09	2.28	11.46	-16.41
Assets	25	25	20	20	6	6	18	18
Quarters	92	92	88	88	65	65	88	88

	CDS		Commod.		FX		All	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	10.10	-23.85	4.69	-1.10	7.19	-13.68	6.60	2.30
	(3.75)	(-2.25)	(1.14)	(-0.27)	(2.15)	(-2.24)	(1.86)	(0.25)
Market	2.57	4.55	-1.08	-1.57	4.83	3.03	1.04	1.64
	(1.20)	(2.24)	(-0.56)	(-1.00)	(1.65)	(1.18)	(0.62)	(0.97)
Intercept	-0.39	-0.12	0.96	0.52	-0.59	-0.59	0.33	0.11
	(-3.14)	(-1.15)	(0.77)	(0.81)	(-0.91)	(-1.02)	(0.49)	(0.23)
R^2	0.64	0.93	0.21	0.05	0.18	0.43	0.50	0.30
MAPE, %	0.19	0.11	1.24	1.35	0.48	0.39	0.72	0.87
MAPE-R, %	0.55	0.28	1.27	1.47	0.65	0.81	0.72	0.87
RRA	2.19	-5.17	1.55	-0.36	2.09	-3.99	2.18	0.76
Assets	20	20	23	23	12	12	124	124
Quarters	47	47	92	92	80	80	92	92

Table 13: **Cross-sectional Asset Pricing Tests by Asset Class: Recent Sample**
Risk price estimates for shocks to the intermediary capital ratio (HKM) or the Adrian et al. (2014a) leverage factor (AEM), and the excess return on the market. Here we focus on the more recent quarterly sample 1990Q1–2012Q4. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	1.38	1.30	1.80	22.67	5.51	-0.51	6.85	3.10
	(1.16)	(0.71)	(1.35)	(0.80)	(3.09)	(-0.39)	(3.51)	(2.10)
Market	0.07	1.44	1.75	2.08	-0.14	0.43	3.03	0.78
	(0.17)	(1.71)	(2.16)	(0.74)	(-0.16)	(0.60)	(1.76)	(1.52)
Intercept	0.59	0.12	0.02	-2.26	-0.16	-0.04	-0.34	-0.19
	(1.68)	(4.39)	(0.06)	(-0.77)	(-3.90)	(-0.21)	(-1.30)	(-1.06)
R^2	0.27	0.78	0.71	0.96	0.72	0.04	0.32	0.70
MAPE, %	0.16	0.05	0.17	0.07	0.07	0.40	0.16	0.28
MAPE-R, %	0.17	0.24	0.40	0.37	0.11	0.55	0.17	0.28
RRA	1.92	1.79	2.39	31.15	7.74	-0.71	10.03	4.30
Assets	25	20	6	18	20	23	12	124
Quarters	516	449	196	310	143	316	407	516

Table 14: **Cross-sectional Tests at the Monthly Frequency**

Risk price estimates for shocks to the intermediary capital ratio and the excess return on the market. The monthly sample is January 1970 to December 2012. The monthly intermediary capital ratio here is the ratio of total market equity (measured monthly) to total market assets (book debt plus market equity) of primary dealer holding companies, where book debt is the latest quarterly observation. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Leverage	0.12	-2.12	0.09	-1.63	0.15	-0.33	0.09	-2.92
	(3.19)	(-1.73)	(1.75)	(-1.81)	(4.41)	(-0.15)	(2.05)	(-2.00)
R^2	0.15	0.08	0.09	0.06	0.21	0.00	0.06	0.16
Assets	25	25	20	20	6	6	18	18
Quarters	168	168	145	145	62	62	100	100
	CDS		**Commod.**		**FX**		**All**	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Leverage	0.14	-1.30	0.00	-0.95	-0.10	0.65	0.10	-1.95
	(3.20)	(-0.49)	(0.18)	(-1.29)	(-2.15)	(0.70)	(3.13)	(-2.02)
R^2	0.21	0.04	0.00	0.06	0.10	0.01	0.16	0.11
Assets	20	20	23	23	12	12	124	124
Quarters	44	44	102	102	132	132	169	169

Table 15: **Predictive Regressions by Asset Class**
One-year-ahead predictive regression results for each asset class. The quarterly sample is 1970Q1–2012Q4. We regress the mean return on all assets of an asset class on lagged intermediary leverage, which is either the squared inverse of the intermediary capital ratio (HKM), or the Adrian et al. (2014a) leverage ratio (AEM). Regression coefficients are multiplied by 100. Hodrick (1992) t-statistics are reported in parentheses.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.07	14.13	5.05	25.47	5.92	19.10	13.34	-112.55
	(0.02)	(2.60)	(3.05)	(1.25)	(1.83)	(0.67)	(3.12)	(-0.37)
Intercept	2.14	0.40	0.40	0.43	0.41	2.14	-4.73	2.73
	(1.63)	(0.26)	(1.78)	(0.93)	(0.51)	(1.08)	(-2.75)	(0.25)
R^2	0.00	0.69	0.83	0.21	0.77	0.57	0.95	0.91
MAPE, %	0.55	0.27	0.13	0.29	0.42	0.55	0.29	0.37
MAPE-R, %	0.53	0.41	0.43	0.38	1.07	2.00	1.01	1.36
RRA	0.03	6.06	1.98	9.98	1.74	5.61	4.51	-38.06
Assets	25	25	20	20	6	6	18	18
Quarters	172	172	148	148	65	65	103	103
	CDS		Commod.		FX		All	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	8.49	-26.24	0.95	2.86	19.30	-26.27	3.45	14.34
	(3.25)	(-2.84)	(0.32)	(0.60)	(3.28)	(-2.27)	(1.08)	(0.90)
Intercept	-0.37	0.49	0.31	0.32	-0.96	-1.51	-0.01	0.10
	(-3.71)	(1.06)	(0.49)	(0.49)	(-1.15)	(-1.62)	(-0.02)	(0.04)
R^2	0.64	0.35	0.00	0.03	0.53	0.37	0.41	0.47
MAPE, %	0.20	0.33	1.39	1.40	0.44	0.49	0.77	0.90
MAPE-R, %	0.21	0.35	1.41	1.62	1.05	1.13	0.77	0.90
RRA	1.92	-5.94	0.33	0.99	7.16	-9.74	1.48	6.15
Assets	20	20	23	23	12	12	124	124
Quarters	47	47	105	105	135	135	172	172

Table 16: **Capital Ratio or AEM Leverage: Single Factor Models**
Risk price estimates for shocks to the intermediary capital ratio (HKM) or the Adrian et al. (2014a) leverage factor (AEM) alone. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	-0.38	5.31	6.22	14.16	9.32	0.94	18.97	3.41
	(-0.14)	(3.10)	(1.77)	(2.99)	(2.91)	(0.31)	(3.44)	(1.07)
Intercept	2.43	0.35	0.39	-5.19	-0.37	0.29	-1.08	-0.03
	(1.79)	(1.68)	(0.48)	(-2.67)	(-3.73)	(0.46)	(-1.38)	(-0.06)
R^2	0.00	0.84	0.72	0.94	0.63	0.00	0.58	0.40
MAPE, %	0.56	0.13	0.46	0.32	0.20	1.39	0.42	0.78
MAPE-R, %	0.54	0.44	1.14	1.02	0.20	1.41	1.05	0.78
RRA	-0.21	2.99	3.12	7.73	4.15	0.50	11.14	1.92
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

(a) **Single Factor Model**

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	5.97	6.62	6.94	28.50	12.96	6.94	19.26	8.69
	(1.89)	(2.55)	(1.52)	(1.71)	(3.00)	(1.77)	(3.40)	(2.39)
Market	1.38	2.17	2.39	2.92	1.62	0.06	8.63	1.74
	(0.89)	(1.15)	(0.60)	(0.54)	(0.56)	(0.03)	(1.81)	(0.97)
Intercept	0.33	0.29	0.27	-1.08	-0.40	0.65	-0.75	-0.22
	(0.24)	(2.23)	(0.22)	(-0.24)	(-2.60)	(0.57)	(-0.68)	(-0.26)
R^2	0.45	0.85	0.74	0.99	0.68	0.26	0.59	0.68
MAPE, %	0.39	0.12	0.43	0.16	0.19	1.22	0.44	0.61
MAPE-R, %	0.48	0.32	0.47	0.76	0.16	1.37	0.51	0.61
RRA	2.14	2.39	2.26	10.09	3.76	2.43	7.34	3.12
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

(b) **Two Factor Model**

Table 17: **Intermediary Equity Return**

The capital factor considered here is the value-weighted equity return of primary dealers. Panel (a) reports risk price estimates for primary dealers' equity return alone, while Panel (b) also includes the excess return on the market. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	7.82	15.53	6.97	28.71	8.13	-1.77	24.69	-82.01
	(3.81)	(3.38)	(3.20)	(0.92)	(3.49)	(-0.18)	(1.39)	(-0.58)
Market	1.59	1.55	4.91	5.31	1.49	5.45	1.50	-1.41
	(2.09)	(2.09)	(2.16)	(1.96)	(0.33)	(2.47)	(1.11)	(-0.26)
R^2	0.59	0.81	2.03	1.35	1.08	1.03	0.98	0.96
MAPE, %	0.34	0.27	0.25	0.15	0.34	0.51	0.16	0.20
MAPE-R, %	0.39	0.29	0.26	0.42	0.43	1.59	0.69	1.17
RRA	3.09	6.13	2.57	10.57	2.35	-0.51	7.94	-26.38
Assets	25	25	20	20	6	6	18	18
Quarters	172	172	148	148	65	65	103	103

	CDS		Commod.		FX		All	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	6.58	-25.99	5.55	3.62	23.74	2.35	9.24	12.11
	(2.58)	(-2.54)	(1.74)	(0.65)	(2.57)	(0.37)	(2.83)	(1.08)
Market	0.34	3.76	1.25	0.60	6.64	-5.50	1.52	1.66
	(0.15)	(1.86)	(0.68)	(0.31)	(1.17)	(-1.47)	(0.92)	(0.95)
R^2	0.22	0.85	0.08	0.04	0.59	0.13	0.71	0.47
MAPE, %	0.26	0.12	1.35	1.40	0.50	0.99	0.62	0.81
MAPE-R, %	0.39	0.29	1.39	1.54	0.63	1.09	0.62	0.81
RRA	1.42	-5.63	1.83	1.19	8.46	0.84	3.65	4.78
Assets	20	20	23	23	12	12	124	124
Quarters	47	47	105	105	135	135	172	172

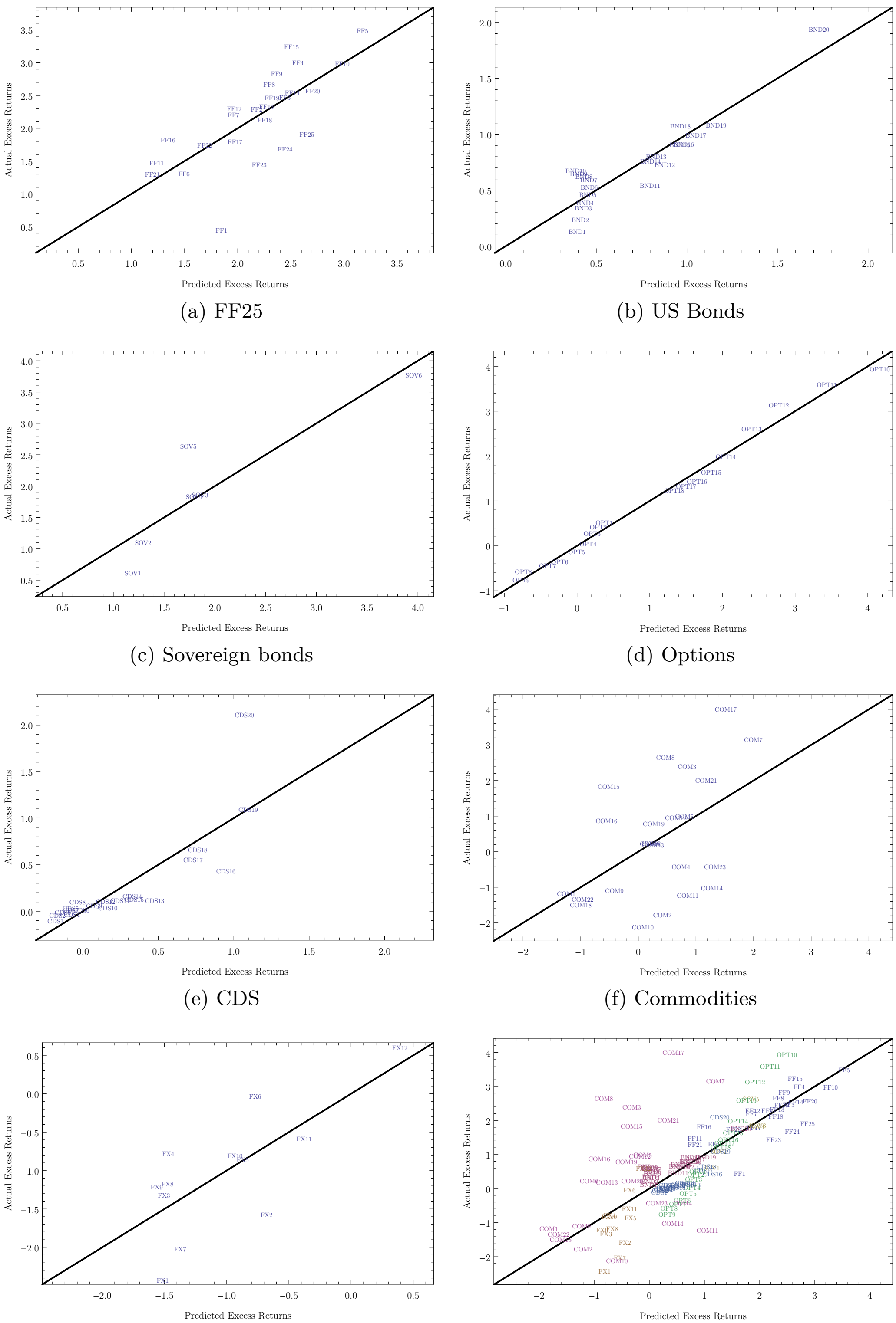
Table 18: **Cross-sectional Tests without an Intercept**

Risk price estimates for shocks to the intermediary capital ratio (HKM) or the Adrian et al. (2014a) leverage factor (AEM), and the excess return on the market, without an intercept in the cross-sectional regression. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	All ex. FF25	FF25+Mom	FF25+Mom	All+Mom	All+Mom	FF25+Intl	FF25+Intl	All+Intl	All+Intl
Capital	12.03	5.37	0.12	7.59	7.55	4.61	5.42	6.55	7.14
	(3.30)	(3.06)	(0.05)	(2.43)	(2.21)	(2.40)	(2.05)	(1.86)	(1.90)
Market	0.61	1.54	-1.02	1.44	1.33	1.65	1.97	1.53	1.73
	(0.33)	(2.13)	(-0.81)	(0.90)	(0.77)	(2.25)	(1.49)	(0.89)	(0.97)
R^2	0.87	0.22	0.12	0.56	0.53	0.15	0.21	0.51	0.62
MAPE, %	0.80	0.61	0.61	0.67	0.68	0.60	0.58	0.68	0.67
RRA	4.66	2.12	0.05	2.99	2.98	1.82	2.14	2.58	2.82
Assets	99	35	35	134	134	46	46	145	145
Quarters	164	172	172	172	172	172	172	172	172
Intercept	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 19: **Other Equities: Momentum Portfolios and International Equities**

Risk price estimates for shocks to the intermediary capital ratio (HKM) or the Adrian et al. (2014a) leverage factor (AEM), and the excess return on the market, with and without an intercept in the cross-sectional regression. The first column combines all portfolios except the Fama-French 25 equities portfolios sorted by size and book-to-market. The second and third use only momentum sorted portfolios and the Fama-French 25. The forth and fifth add momentum portfolios to our benchmark All portfolios test. The sixth and seventh add country-level equity portfolios (from Global Financial Data) alongside the Fama-French 25. The last two columns add these global equity portfolios to the benchmark All portfolios test. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The intermediary capital ratio is the ratio of total market equity to total market assets (book debt plus market equity) of primary dealer holding companies. Shocks to capital ratio are defined as AR(1) innovations in the capital ratio, scaled by the lagged capital ratio. The AEM leverage factor is defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.



(a) FF25 (b) US Bonds

(c) Sovereign bonds (d) Options

(e) CDS (f) Commodities

(g) FX (h) All Portfolios

Figure A.1: **Pricing Errors**

Actual average percent excess returns on tested portfolios versus predicted expected returns using their risk exposures (betas) with respect to shocks to the intermediary capital ratio and the excess return on the market. Test portfolios are abbreviated based on their asset class: equities (FF), US bonds (BND), foreign sovereign bonds (SOV), options (OPT), CDS, commodities (COM), and foreign exchange (FX).

Primary Dealer	Start Date	End Date	Primary Dealer	Start Date	End Date
ABN Amro	9/29/1998	9/15/2006	HSBC	5/9/1994	Current
Aubrey Lanston	5/19/1960	4/17/2000	Hutton	11/2/1977	12/31/1987
BA Securities	4/18/1994	9/30/1997	Irving	5/19/1960	7/31/1989
Banc One	4/1/1999	8/1/2004	Jefferies	6/18/2009	Current
Bank of America	5/17/1999	11/1/2010	JP Morgan	5/19/1960	Current
Bank of America	11/17/1971	4/15/1994	Kidder Peabody	2/7/1979	12/30/1994
Bank of Nova Scotia	10/4/2011	Current	Kleinwort Benson	2/13/1980	12/27/1989
Bankers Trust	5/19/1960	10/22/1997	Lehman	11/25/1976	9/22/2008
Barclays	4/1/1998	Current	Lehman	2/22/1973	1/29/1974
Barclays De Zoete Wedd	12/7/1989	6/30/1996	LF Rothschild	12/11/1986	1/17/1989
Bartow Leeds	5/19/1960	6/14/1962	Lloyds	12/22/1987	4/28/1989
Bear Stearns	6/10/1981	10/1/2008	Malon Andrus	5/19/1960	11/24/1965
Becker	11/17/1971	9/10/1984	Manufac. Hanover	8/31/1983	12/31/1991
Blyth	4/16/1962	1/14/1970	Merrill Lynch	5/19/1960	2/11/2009
Blyth Eastman Dillon	12/5/1974	12/31/1979	Merrill Lynch	11/1/2010	Current
BMO	10/4/2011	Current	MF Global	2/2/2011	10/31/2011
BMO Nesbitt	2/15/2000	3/31/2002	Midland-Montagu	8/13/1975	7/26/1990
BNP Paribas	9/15/2000	Current	Mizuho	4/1/2002	Current
BNY	8/1/1989	8/9/1990	Morgan Stanley	2/1/1978	Current
Brophy, Gestal, Knight	5/8/1987	6/19/1988	NationsBanc	7/6/1993	5/16/1999
BT Alex Brown	10/23/1997	6/4/1999	Nesbitt Burns	6/1/1995	2/14/2000
BZW	7/1/1996	3/31/1998	Nikko	12/22/1987	1/3/1999
Cantor Fitzgerald	8/1/2006	Current	Nomura	12/11/1986	11/30/2007
Carroll McEntee	9/29/1976	5/6/1994	Nomura	7/27/2009	Current
CF Childs	5/19/1960	6/29/1965	Northern Trust	8/8/1973	5/29/1986
Chase	7/15/1970	4/30/2001	Nuveen	11/18/1971	8/27/1980
Chemical	5/19/1960	3/31/1996	NY Hanseatic	2/8/1984	7/26/1984
CIBC	3/27/1996	2/8/2007	Paine Webber	11/25/1976	12/4/2000
Citigroup	6/15/1961	Current	Paine Webber	6/22/1972	6/27/1973
Continental	5/19/1960	8/30/1991	Paribas	5/1/1997	9/14/2000
Country Natwest	9/29/1988	1/13/1989	Pollock	5/19/1960	2/3/1987
Countrywide	1/15/2004	7/15/2008	Prudential	10/29/1975	12/1/2000
Credit Suisse	10/12/1993	Current	RBC	7/8/2009	Current
CRT	12/22/1987	7/5/1993	RBS	4/1/2009	Current
Daiwa	12/11/1986	Current	REFCO	11/19/1980	5/7/1987
Dean Witter Reynolds	11/2/1977	4/30/1998	Robertson Stephens	10/1/1997	9/30/1998
Deutshe Bank	12/13/1990	Current	Salomon Smith Barney	5/19/1960	4/6/2003
Dillon Read	6/24/1988	9/2/1997	Sanwa	6/20/1988	7/20/1998
Discount Corp.	5/19/1960	8/10/1993	SBC	3/29/1990	6/28/1998
DLJ	3/6/1974	1/16/1985	Second District	6/15/1961	8/27/1980
DLJ	10/25/1995	12/31/2000	Securities Groups	5/19/1960	6/5/1983
Dresdner Kleinwort	5/8/1997	6/26/2009	Security Pacific	12/11/1986	1/17/1991
Drexel Burnham	5/19/1960	3/28/1990	SG Americas	2/2/2011	Current
DW Rich	5/19/1960	12/31/1969	SG Cowen	7/1/1999	10/31/2001
Eastbridge	6/18/1992	5/29/1998	SG Warburg	6/24/1988	7/26/1995
FI Dupont	12/12/1968	7/18/1973	Smith Barney	8/22/1979	8/31/1998
First Boston	5/19/1960	10/11/1993	Souther Cal. S&L	6/7/1983	8/5/1983
First Chicago	5/19/1960	3/31/1999	TD	2/11/2014	Current
First Interstate	7/31/1964	6/17/1988	Thomson McKinnon	12/11/1986	7/7/1989
First N.B. of Boston	3/21/1983	11/17/1985	UBS	12/7/1989	Current
First Pennco	3/7/1974	8/27/1980	Weeden	6/17/1976	5/15/1978
Fuji	12/28/1989	3/31/2002	Wertheim Schroder	6/24/1988	11/8/1990
Goldman Sachs	12/4/1974	Current	Westpac Pollock	2/4/1987	6/27/1990
Greenwich	7/31/1984	4/1/2009	White Weld	2/26/1976	4/18/1978
Harris	7/15/1965	5/31/1995	Yamaichi	9/29/1988	12/4/1997
			Zions	8/11/1993	3/31/2002

Table A.1: **Primary Dealers, 1960–2014**

The New York Federal Reserve Bank's list of primary dealers. We have condensed the list slightly by combining entries that differ due to name changes but maintain continuity in primary dealer role, most commonly due to the dealer acquiring another firm. However, we continue to list acquisition targets or merged entities separately for the period that they appear on the dealer list prior to acquisition.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	2.11	-1.54	6.55	10.11	7.65	2.36	-9.14	2.36
	(1.53)	(-0.33)	(2.07)	(2.18)	(2.59)	(1.62)	(-1.06)	(1.33)
Market	-1.72	4.81	-1.00	2.32	0.54	-1.35	13.26	1.57
	(-1.33)	(1.19)	(-0.34)	(0.91)	(0.19)	(-0.74)	(2.08)	(0.96)
Intercept	3.93	0.32	1.20	-0.44	-0.38	0.78	-2.84	0.15
	(3.39)	(4.36)	(2.15)	(-0.21)	(-3.46)	(1.12)	(-1.90)	(0.23)
R^2	0.10	0.82	0.95	0.97	0.69	0.11	0.72	0.37
MAPE, %	0.52	0.13	0.17	0.18	0.18	1.27	0.37	0.76
MAPE-R, %	0.73	0.24	0.91	0.85	0.36	1.33	1.07	0.76
RRA	8.63	-7.38	20.39	39.31	16.41	9.12	-43.97	9.66
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table A.2: **Book Equity instead of Market Equity**

Risk price estimates for shocks to the intermediary capital ratio and the excess return on the market. Here, the capital ratio is defined as the ratio of total *book* equity to total *book* assets of primary dealer holding companies. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. Mean absolute pricing error (MAPE) is in percentage terms. MAPE-R uses a restricted model which restricts the risk prices (λs) to be the same in all asset classes, as in the last column. Relative risk aversion (RRA) is implied by the price of intermediary capital risk factor and the factors covariance matrix. GMM t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.