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: intermediary asset pricing, primary dealers, intermediary capital, cyclical leverage

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1 Introduction

Intermediary asset pricing theory offers a new perspective for understanding risk premia. These theories are predicated on the fact that the intermediary sector—such as the primary dealer sector that we study here—is in the advantageous position of trading almost all asset classes, anytime and everywhere. It is thus 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. Households' comparative lack of expertise in trading assets, especially sophisticated ones like derivatives or commodities, casts doubt on the viability of household marginal utility of as a unified model for jointly pricing the wide array of traded assets in the economy. 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.[1]

Our second choice is guided by the recent intermediary asset pricing models of He and Krishnamurthy (2013, 2012) and Brunnermeier and Sannikov (2014), which follow the tradition of Bernanke and Gertler (1989) and Holmstrom and Tirole (1997). In these models, 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.

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

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 TFP-style persistent technology shocks that drive 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 the 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

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

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 plausibility that (i) intermediaries are marginal pricers in many markets and (ii) their equity capital ratio is a sensible proxy for their marginal value of wealth. In particular, if we find large disparities in intermediary capital risk prices across markets, it suggests that (i) and/or (ii) is violated.[2]

[2] Our tests are also potentially informative about the assumption of homogeneity among intermediaries, which is implicit in essentially all intermediary asset pricing models. If intermediaries with heterogeneous pricing kernels specialize in specific asset classes, the risk prices identified in different markets may differ. We view this as a plausible explanation for the small discrepancy of risk prices that we estimate from different markets, but our empirical approach is not designed to test this hypothesis.

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 magnitude, 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 by non-primary dealers (who tend to be smaller, standalone broker-dealers) or non-financial firms, we find highly variable risk prices estimated from different asset classes that are largely insignificant and often with 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 that assets that pay more in states with a low intermediary capital ratio (those with low betas on η_t shocks) are the same assets that yield lower expected returns in equilibrium. This reveals that low capital-risk-beta assets are viewed as valuable hedges by marginal investors, or in other words 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 when their capital is impaired.[3] Our risk price estimates also suggest that intermediary equity capital ratios are pro-cyclical, or equivalently, that intermediary leverage is counter-cyclical (for primary dealers).

The second economic implication arises from the similarity in magnitudes of capital ratio risk prices estimated from different asset classes. Our pricing kernel construction based on a single aggregate capital ratio (as opposed to heterogeneous ratios among intermediaries), implicitly assumes that one set of intermediaries is marginal in all classes.[4] This assumption also predicts that the estimated price of capital ratio risk should be the same in all asset classes. Our cross-asset empirical results are not far from this theoretical prediction. The risk price estimated jointly from all asset classes is 10% per quarter. When we instead estimate the risk price independently from each asset class, we find that five of the seven estimates are between 7% and 11%. For options and FX portfolios, the estimated risk prices are 22% and 19%, respectively. Though we reject the null of 0% in all seven markets,[5] we cannot reject the null of 10% in any individual market. This fact is surprising and quite striking. One might expect that trading in different asset classes involves

[3]Examples include Gabaix et al. (2007), Froot and O'Connell (1999), and Siriwardane (2015).

[4]Different intermediaries can be marginal in each asset class, as long as their capital ratios are highly correlated.

[5]In the FX market, we find a GMM 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.

substantially different knowledge, terminology, and expertise; and yet these markets all produce estimated prices of intermediary capital risk that are statistically indistinguishable.

An important pre-cursor of our paper is Adrian et al. (2014a) (henceforth AEM), which is the first paper to unite the intermediary-based paradigm with mainstream empirical asset pricing. Our identification of a 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 for intermediary marginal value of wealth, which is the intermeidary's pricing kernel that we are after. The results reported in AEM are based on test portfolios comprised of stocks and government bonds. When we perform our test pooling all seven asset classes and replacing 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 in these cases the opposite-sign estimate is statistically significant.

We explore the differences between our analysis and AEM that may be responsible for conflicting results in Section 4. Our papers differ in the identity of financial intermediaries and data sources. AEM focus on the definition of the security broker-dealer sector and associated book leverage ratios provided in the Federal Reserve's Flow of Funds. Our definition instead uses the New York Fed's primary dealers and data on their holding companies from Compustat/CRSP and Datastream to construct a market equity capital ratio.

We find little evidence that the accounting treatment of book versus market leverage drives these differences.[6] 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 from the holding company level. The distinction between these two approaches rests on the role of internal capital markets within bank holding companies. Consider, for example, our treatment of JP Morgan Securities LLC, which is one of the largest broker-dealers in the world

[6]We discuss this possibility in Section 4. Because book assets of broker-dealers are marked-to-market, the wedge between their book and market values is quite small. We reinforce this view empirically by showing that book leverage and market leverage in our primary dealer sample move closely together over business cycles.

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. However, if the 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 business (for example in its large mortgage lending activities) may be enough to 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 its 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. While it is generally difficult to measure capital flows within financial conglomerates, we provide 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 that capital is fungible within broker-dealer holding companies, in support of the idea that holding company leverage is the economically important one.

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.

1.1 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, 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, 2013, 2012; Brunnermeier and Sannikov, 2014).[7] Of course, while the equity market sees greater direct participation by households, the pricing kernel of intermediaries remains informative as long as intermediaries are marginal (unconstrained).[8]

Gabaix et al. (2007) study a cross-section of prices in 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); Garleanu et al. (2009) present similar evidence for index options. AEM is the first paper providing systematic empirical support for intermediary asset pricing theory in classic cross-sectional pricing tests. Adrian et al. (2014b) extends the AEM evidence by demonstrating that broker-dealer leverage possesses significant time series forecasting power for returns on stocks and bonds.

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 with the marginal investor being a consumer household. These models implicitly view intermediation as a pure pass through, and asset markets are studied as direct interactions among households without loss of generality. By contrast, intermediary asset

[7] Related theoretical papers include Allen and Gale (1994), Basak and Cuoco (1998), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) Geanakoplos and Fostel (2008), Adrian and Shin (2010), Xiong (2001), Kyle and Xiong (2001), Vayanos (2004), Pavlova and Rigobon (2007), Adrian and Boyarchenko (2012); Adrian and Shin (2014)

[8] Conceptually, if households are marginal investors in the equity market and households' pricing kernel is accurately measured, it should also succeed in pricing the cross section of equities, 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.

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 "specialist" 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 would fail to price assets in those markets. For these same markets, specialist intermediaries take over the role of marginal trader, raising the possibility that their marginal value of wealth would better succeed as an empirical pricing kernel.[9]

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. However, the exact functional form in (2) arises from existing theories under appropriate assumptions. This functional form is intuitive: 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 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 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

[9] At the same time, the participation of households in less sophisticated markets (like that of equities) in no way precludes financial intermediaries from also being marginal, so that the intermediary kernel should plausibly price assets in these markets as well.

falls. It captures the intuition that an intermediary's risk bearing capacity is inhibited when its equity capital falls—risk aversion drives up its 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 plausible 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.[10]

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 that govern soundness of the financial intermediary sector via η_t. This second factor directly affects may capture agency/contracting frictions in the intermediation business, regulator considerations, or shocks to one portion of the intermediary portfolio that affect their broader risk bearing capacity (e.g., the housing market collapse in 2007-09).[11] This view is consistent with Muir (2014) who shows that the asset pricing behavior is markedly different during "fundamental" disaster episodes (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, 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

[10] Many of the largest primary dealers in our sample are constrained by Basel capital requirements (Kisin and Manela, 2013), and potentially also by the SEC's net capital rule. Capital constraints are particularly costly during liquidity crises (Kashyap et al., 2008; Hanson et al., 2011; Koijen and Yogo, forthcoming; Kisin and Manela, 2013).

[11] 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).

implies

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

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 variance and beta:

$$\sigma_{W,t}^2 dt = Var_t\left[\frac{dW_t}{W_t}\right],\ \beta_{W,t}^i = \frac{\mathbb{E}_t\left[dR_t^i \cdot (dW_t/W_t)\right]}{Var_t\left[dW_t/W_t\right]},$$
$$\sigma_{\eta,t}^2 dt = Var_t\left[\frac{d\eta_t}{\eta_t}\right],\ \beta_{\eta,t}^i = \frac{\mathbb{E}_t\left[dR_t^i \cdot (d\eta_t/\eta_t)\right]}{Var_t\left[d\eta_t/\eta_t\right]}.$$

Equation (3) is the two-factor pricing model that guides 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 marginal value of wealth Λ_t; hence, the higher an asset's covariance with either factor, the higher the equilibrium return that the asset must promise to compensate its investor, all else equal.

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 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.[12] 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 both capture 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 the its wealth share.[13] For instance, He and Krishnamurthy (2012, 2013) assume that risky assets are held directly only by the intermediary sector. 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.[14] 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. 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

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

[13] In He and Krishnamurthy (2012, 2013), households can 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.

[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.

holds in Brunnermeier and Sannikov (2014), which allows households to manage risky assets at some exogenous holding cost.[15]

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 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.[16]

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 number of firms represents essentially all of the broker-dealer sector by size, a substantial share of the broader banking sector, and is even large relative to the entire publicly traded sector.[17] Below, we use "primary dealer" and "intermediary" interchangeably whenever there is no ambiguity in the context.

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

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

[15]In Brunnermeier and Sannikov (2014), a series of negative shocks impairs the capital of intermediaries leading them to reduce their borrowing and shed assets and by selling them 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.

[16]Cheng et al. (2015) also focus on primary dealers in their study of executive compensation in financial firms.

[17]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 that not classified as broker-dealers, for instance JP Morgan.

where firm i is a NY Fed primary dealer designee during quarter t. We use book value of debt to proxy for the unobserved market value of debt, as customary in corporate finance. Importantly, 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.

We plot the intermediary capital ratio, which runs from 1970 to 2012, in Figure 1 (shaded areas indicate 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 affecting certain asset markets (e.g., options) but not the entire stock market.

We construct the capital ratio growth rate, which we denote as η_t^Δ and is the key input into our cross section tests, as follows. We estimate a shock to the capital ratio in levels, u_t, as an innovation in the autoregression $\eta_t = \rho_0 + \rho\eta_{t-1} + u_t$, and convert this to a growth rate by dividing by the lagged capital ratio

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

Figure 1 plots η_t^Δ, and Table 3 shows the bivariate correlations between this intermediary capital risk factor and an array of aggregate macro variables. Specifically, we compare to the S&P 500 earnings-to-price ratio from Shiller, 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 the comparison 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 high unemployment rate, decreases in GDP growth, a deterioration in financial conditions (based on the Chicago Fed index), or increased realized volatility. Table 3 also presents the bivariate correlations among levels of these correponding variables, which still shows the pro-cyclicality of our intermediary capital ratio.

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 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 bond portfolios, we include government and corporate bond portfolios in the same class.[18] We use ten maturity-sorted government bonds 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 options, we use 54 portfolios of S&P 500 index options sorted on moneyness and maturity from Constantinides et al. (2013), split by contract type (27 call and 27 put 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.*"

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 et al. (2014). Second is the set of six currency portfolios sorted on momentum from Menkhoff et al. (2012). We use the sample period intersection of these datasets, covering March 1976 to January 2010.[19]

For commodities, we include 24 commodity futures returns studied in Koijen et al. (2013). The

[18] 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.

[19] 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 use only one of the two data sets.

commodities series include six energy products, eight agricultural crops, three livestock, and seven metals. We use the sample during which all futures returns are non-missing, which begins in 2002.

CDS is the only asset class for which we do not have portfolio returns from pre-existing studies. To fill this gap, we construct 20 portfolios sorted by spreads using individual name 5-year CDS. The data are from Markit and begin in 2001. We focus on 5-year CDS contracts 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 (in the case of no default) is

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

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 is approximates the log capital gain of the short position.[20]

We also consider tests in which all portfolios are gathered into a single large cross-section. Because some asset classes like 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 Fama-French portfolios have an average time-series intermediary capital beta (β_η) of 0.07, with a

[20]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 CDS spread as $\lambda = 4\log(1+CDS/4L)$, where CDS is the five year CDS 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 Gurkaynak, Sack, and Wright, 2007). Risk-free rates are interpolated with a cubic function to find rates for each quarter.

standard deviation of 0.11 across the 25 portfolios. The last two columns show in the pool of all asset classes, the dispersion in β_η is even higher, with a mean of 0.1 and standard deviation of 0.15.

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 seven asset classes—US equities, US government and corporate bonds, sovereign bonds, CDS, options, commodities, and FX—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, $R^{i_k}_{t+1} - r^f_t$, on the intermediary capital risk factor, η^Δ_{t+1}, and on the excess return of the market portfolio, $R^W_{t+1} - r^f_t$:[21]

$$R^{i_k}_{t+1} - r^f_t = a^{i_k} + \beta^{i_k}_\eta \eta^\Delta_{t+1} + \beta^{i_k}_W \left(R^W_{t+1} - r^f_t \right) + \epsilon^{i_k}_{t+1}. \tag{7}$$

We then run a cross-sectional regression across 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^k_η and λ^k_W:[22]

$$\hat{\mathbb{E}} \left[R^{i_k}_{t+1} - r^f_t \right] = \gamma_k + \lambda^k_\eta \hat{\beta}^{i_k}_\eta + \lambda^k_W \hat{\beta}^{i_k}_W + \nu^{i_k}. \tag{8}$$

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

[21] Notice that the model (3) is in the conditional form. 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 (8) is 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).

[22] The cross section regressions in (8) include the constant γ_k. Section 5.5 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 Fama-MacBeth (1973) t-statistics (t-FM) that correct for return cross-correlation as well as GMM t-statistics (t-GMM) that correct for cross-correlation and first-stage estimation error in betas (as advocated by Cochrane (2005)). 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). It is interesting to note that in our main bivariate specification, the estimated price of risk on the market portfolio is positive in all asset classes, though it is significant only in the FX test.

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 one asset class at the 5% level, and in all classes at the 10% (the GMM t-statistic based on six sovereign bond portfolios is 1.66). The model provides the closest fit for option portfolios (R^2 of 93%) and the weakest fit for commodities (R^2 of 44%).

The last column of Table 5 reports results when all 161 portfolios from seven asset classes are included simultaneously in the cross section test. The estimated price of intermediary capital risk is 10% per quarter with a GMM t-statistic of 2.78 and R^2 of 49%. This risk price estimate is economically large. For example, the cross section standard deviation in intermediary capital growth betas for the all portfolios case is 0.15 (see Table 4). Thus, a one standard deviation difference in the capital risk beta of two assets corresponds to a difference of $0.15 \times 0.10 \times 4$, or 6.0 percentage points, in their annual risk premium.

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. We also compare our results to the Fama-French (1993) three-factor model.[23] When we simultaneously control for the market excess return, SMB, and HML in our "all portfolios" test, we estimate an intermediary capital risk price of 12% per quarter (with a GMM t-statistic of 3.23), or 20% larger

[23] Because our capital ratio factor is non-traded and theoretically motivated, the statistically oriented Fama-French model is not a natural benchmark 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.

than the estimate in our baseline two-factor specification. The estimated risk prices on all three Fama-French factors are positive but are statistically insignificant in this test.

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?

Theoretically, if (2) is indeed an appropriate pricing kernel for all asset classes, then the price of risk from each asset class should be the same (up to sampling error). Risk prices are determined solely by the pricing kernel of marginal investors, and therefore must be invariant with respect to the attributes of the assets it is pricing. This is trivially evident from the Euler equation, which implies a functional form for risk prices that is independent of the specific asset in question:

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

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 asset 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 shifting 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 indeed imposes that risk prices are equal across asset classes. Figure 2 compares intermediary risk prices from different asset classes, and also compares with the "all portfolios" estimate, to illustrate the impressive similarity in estimates across tests. Formally, our GMM test cannot reject the hypothesis that the estimated risk price is equal to 10% per quarter (the value found in the "all portfolios" case) for *any* of the individual asset classes. 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. Also implicit in these assumptions is a degree of homogeneity in the pricing kernels of individual financial intermediaries. The homogeneity assumption is the most standard and also perhaps the most tenuous. Its failure could potentially explain the somewhat higher options and FX point estimates, if intermediaries that specialize in trading these instruments differ in some way from other intermediaries (see for example Gârleanu et al., forthcoming).

3.2.3 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)—and exclude firms that are designated NY Fed primary dealers. This definition, which we refer to as "non-primary" dealers, includes firms like Blackrock, GAMCO, and Waddell & Reed. As shown in Table 2, non-primary dealers are small relative to primary dealers.

In Panel (a) of Table 6, 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 prices of capital risk in other asset classes are either insignificant or having wrong signs.

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 6 provides additional indirect evidence supporting our assumption that primary dealers are pricing-relevant financial intermediaries.

3.2.4 Which is more important for pricing, equity or debt?

Innovations in our measure of intermediary capital ratio are driven by either changes in market value of equity or changes in book debt. 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 shocks to $\ln \eta_t = \ln \frac{E_t}{E_t+D_t}$, 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 term), we have[24]

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

As a result, our 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 price of the debt growth rate shock should be negative.[25]

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 excluded from the $t+1$ growth rate calculation, and if it exits at $t+1$ then its market equity is included in the growth rate (likewise for debt).[26]

The results are presented in Table 7. 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 of intermediary equity risk is 10% per quarter. Overall, the pricing ability of intermediary equity is similar, but somewhat weaker, than that of

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

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

[25]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 7.

[26]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.

the capital ratio variable. The estimated price on book debt innovations is negative in six out of seven asset classes, as we expect given our theory and the negative functional relation between debt shocks and capital ratio shocks. However, the magnitudes are often small and insignificant. For the all portfolios test, the intermediary debt risk price is -2% per quarter and is insignificant.

In sum, these results suggest that while book debt innovations play some role in our main pricing results, it is the market equity component of the capital ratio that is most important for the effects that we document.

4 Comparison with AEM: Theory and Data

4.1 Brief review of AEM

AEM is an important pre-cursor of 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 25 Fama-French equity portfolios, 10 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 (2013, 2012) 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 3a vividly 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 3b 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.

4.2 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.[27]

Table 8 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 essentially 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 10% is economically small. From Table 9, the standard deviation in AEM leverage betas

[27] We thank Tyler Muir for sharing data, which is available at `http://faculty.som.yale.edu/tylermuir/LEVERAGEFACTORDATA_001.txt`.

across all portfolios is 0.05, implying differences in annual AEM leverage premia of $0.05 \times 0.10 \times 4$, or 2.0 percentage points, for a one standard deviation difference in beta (or one third of the risk premium effect that we find for our intermediary capital factor). Figure 4 illustrates the extent of inconsistency in AEM pricing performance across asset classes, which contrasts starkly with the capital ratio model results in Figure 2.

We next consider a three-factor horse-race specification that includes our capital ratio factor and the AEM leverage factor together (along with the market return). Table 10 reports the estimation results for each asset class. In the equity market, the presence of AEM renders the capital ratio insignificant, reiterating the strong pricing power of AEM for the US equity market. In all other asset classes, the price of intermediary capital risk is at least 6% per quarter, and only loses statistical significance in the options market. The options market is an interesting case; in the horse-race specification, the lack of statistical significance for our measure appears due to the large and significant *negative* price of risk on the AEM factor.

Our emphasis on a variety of asset classes is the key empirical feature that distinguishes our paper from AEM. 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 household investors. By contrast, financial intermediaries play a central role in the market for derivatives and OTC assets. Our paper provides supporting evidence that this distinction is important for understanding the behavior of a wide variety of assets.

4.3 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 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.[28]

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 in this section.

4.3.1 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. 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 and use firms' most recently published book value of debt from accounting statements. 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.[29] 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.[30]

An advantage of our data set is that we have access to both book and market equity values. This allows us to construct both book and market capital ratios for our primary dealer sample,

[28]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).

[29]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.

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

and investigate whether drastic differences in the two measures can potentially reconcile differences in our findings with AEM. For example, a negative correlation between book and market leverage in our sample, surprising though such a finding might be, could help explain the conflicting risk prices estimated in our study and that of AEM.[31] However, we find that the market capital ratio of primary dealers is in fact strongly positively associated with book capital ratio. They share a correlation of 50% in levels and 30% in innovations, indicating qualitatively similar behavior between them. This is also illustrated in the time series plot of Figure 3b.

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.

4.3.2 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. 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

[31] Previous literature such as Adrian et al. (2014b); 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.

company as the observation of interest.[32]

The holding companies of primary dealers also often hold significant commercial banking businesses,[33] making the distinction between holding company and broker-dealer arm potentially huge. 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 3.2.3) than that of primary dealers. We find that the AEM implied capital ratio and that of our primary dealer sample are strongly negatively correlated at -59%. Yet 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 3.2.3, 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. Two anecdotes support this view.

The first is the 2008 failure of Lehman Brothers. The bankruptcy examiner report describes Lehman Brothers Holdings as a "central banker" for Lehman subsidiaries (Valukas, 2010, Vol. 5, p. 1944). Its broker-dealer units (the European one in particular) required significant funding in their efforts to unwind its prime brokerage services in the days immediately prior to the September 15, 2008 bankruptcy filing. The holding company attempted to avoid bankruptcy by using its liquid non-broker-dealer assets to guarantee the obligations of its broker-dealer subsidiaries for the clearing banks. This glimpse at the internal markets of a large financial institution at the peak

[32] 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.

[33] 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.

of its financial distress indicate the fungibility of capital within broker-dealer holding companies. This point is further corroborated in the bankruptcy case of the Drexel Burnham Lambert Group in 1990, which led to the liquidation of its 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 initiate group-wide risk assessments for all financial institutions with significant broker-dealer subsidiaries.[34]

Of course, if the internal capital markets within the holding company are not well-functioning, 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 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.

4.4 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 model, which we dub either "equity constraint" or "debt constraint" models.

The equity constraint framework originates with net worth-based based models such as Bernanke 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 general 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, 2013, 2012; Brunnermeier and Sannikov, 2014). In other words, from the standpoint of the intermediary,

[34] 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.

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.[35] 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 which is 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 by a lower allowable leverage, and this triggers deleveraging and fire-sales during which assets are sold to some second-best users at a lower equilibrium price. This directly implies that leverage is pro-cyclical in these models—debt falls in those states where debt constraints bind the most and intermediary marginal value of wealth is highest. This corresponds to a positive price for leverage risk, or a negative price of capital ratio risk.

The fact that different intermediary models give opposing predictions is perhaps unsurprising, given the spectrum of complexities in real world financial intermediation that these models may be attempting to describe. 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. A related possibility is that these two models describe different intermediary subsectors that interact in financial markets. He et al. (2010) and Ang et al. (2011) describe one example that supports this view. During a downtown, when marginal value of wealth is likely to be high for all investors, hedge funds (who are perhaps closer to the intermediary in a debt constraint model) sell their assets to commercial banks (who may be better described by equity constraint models), and the leverages of these two sectors move in the opposite directions. Indeed, 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 use this to guide construction of a more sophisticated pricing kernel that nests both mechanisms in a state-dependent manner. And, ultimately, it is an empirical question whether our capital risk factor, the AEM leverage factor, or some combination is the most useful representation of the pricing kernel.

[35] Other related papers are Geanakoplos and Fostel (2008), Adrian and Boyarchenko (2012) and Moreira and Savov (2013).

5 Robustness

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

5.1 Pre-crisis and post-1990 subsamples

Table 11 presents the performance of our intermediary capital risk factor and AEM leverage factor in the 1970Q1–2006Q4, 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. 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 10% per quarter, identical to that in the full sample and highly significant.

We separately investigate the recent sample beginning in 1990 in Table 12. The capital risk price estimate remains 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 the accounting Flow of Funds 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 could 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 take advantage of this opportunity to repeat our cross section analysis at the monthly frequency.

Table 13 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 and US bonds, but remains economically meaningful in the other five asset classes. In the "all portfolios" test, the risk price estimate is 4% per month and highly statistically significant.

Our use of using 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 varation in book debt plays a role in driving the prcing power of our intermediary capital risk factor. From Table 7 in Section 3.2.4 we observe that book debt growth does possess some pricing power, which suggests a potential explanation for the relatively weak monthly performance for our intermediary capital risk factor.

5.3 Time-series return predictability

A common prediction of dynamic intermediary asset pricing models is that the risk premium is time-varying, implying predictability in asset returns based on lagged state variables that captures financial distress. We perform time-series predictive regression in each asset class to evaluate this prediction.

Our setting requires more structure to derive the time-varying risk premium, which is typically a nonlinear 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

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

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 in class on the lagged inverse of the squared intermediary capital ratio

$$R_{t\to t+4}^k - r_t^f = a_k + b_k\frac{1}{\eta_t^2} + u_{t\to t+4}. \tag{12}$$

The model predicts a positive b_k coefficient in Equation (11), as a low intermediary capital ratio (high leverage) state positively predicts the asset's expected future returns. The model's prediction is generally supported by Table 14, which reports a significantly positive $\hat{b}_k$ for five of the seven asset classes at the 10% significance level, and in four classes at the 5% significance level.

The dependent variable in the last column of Table 14 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 2.92.[36]

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 is significant in five 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 15 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. This result is consistent with the horse-race outcomes in Table 10 where AEM leverage factor beats our capital ratio factor exactly in the equity market. But, for all other asset classes, our primary dealers' capital ratio consistently carries a positive and significant price, while the AEM leverage factor keeps producing price estimates with opposite signs for CDS, Options, and FX markets. The take-away is basically the same as from the baseline two-factor model.

Intermediary equity return There is another important single factor model that can be considered as a direct test of He and Krishnamurthy (2012, 2013). 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,

[36] Test statistics in Table 14 use Hodrick (1992) standard errors to adjust for the fact that annual returns are being forecast using overlapping monthly observations.

a result that holds exactly for log preferences.[37] As a result, a similar derivation as in equation (3) implies that the return on the intermediary's equity should be enough to capture the relevant pricing kernel. Given that we are focusing on primary dealers as the marginal financial intermediary, we can construct the value-weighted equity return for the primary dealer sector and perform the standard cross-sectional test, again for all asset classes. This measure is the same as the intermediary (market) equity growth rate constructed in Section 3.2.4, with the same treatment to correct for "entry and exit" in the primary dealer list.

In Table 15, for each asset class, the bottom panel reports the estimated price for the factor of the primary dealers' equity return. Again, except for the Fama-French 25 portfolios, we obtain a significantly positive price for the primary dealers' equity return.[38] This offers another solid supporting evidence for intermediary asset pricing models, which argue that intermediaries are more relevant for more sophisticated asset classes.

5.5 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 16 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 mostly improves.

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,

[37]This is because the pricing kernel is just the marginal investor's marginal utility of consumption, and the consumption of log investors is always a constant fraction of their wealth. If the representative intermediary has recursive preferences, then the future market prospect will in general enter the intermediary's pricing kernel, suggesting some reduce-form specification in line with (2).

[38]In unreported results, we find that by including the market return, a two-factor structure basically recovers results that are similar to our baseline results in Table 5. This suggests that the primary dealers' equity return plays a similar role as the capital risk factor.

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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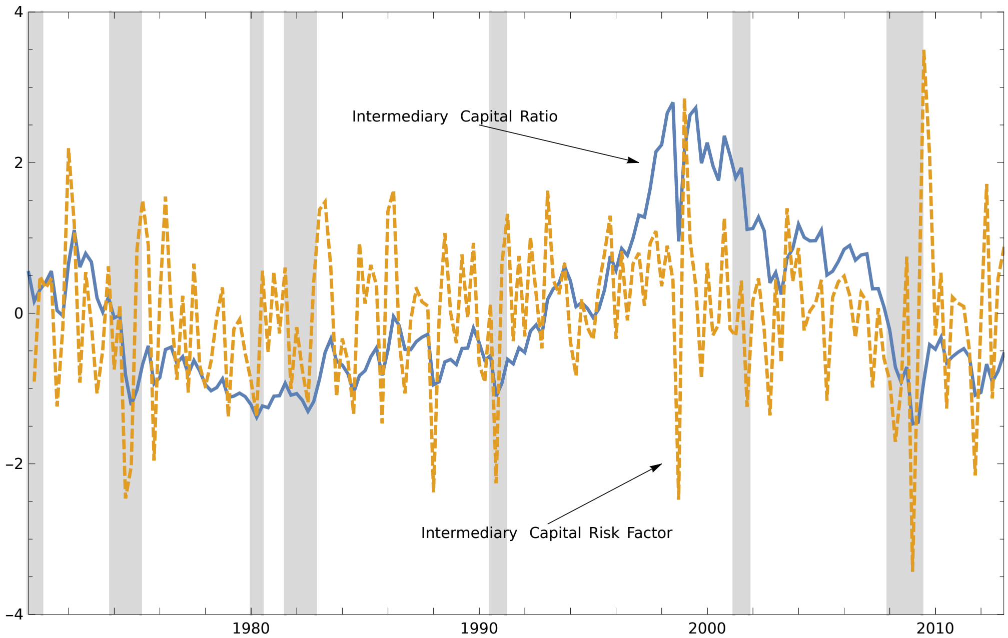


Figure 1: **Intermediary Capital Ratio and Risk Factor**

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.

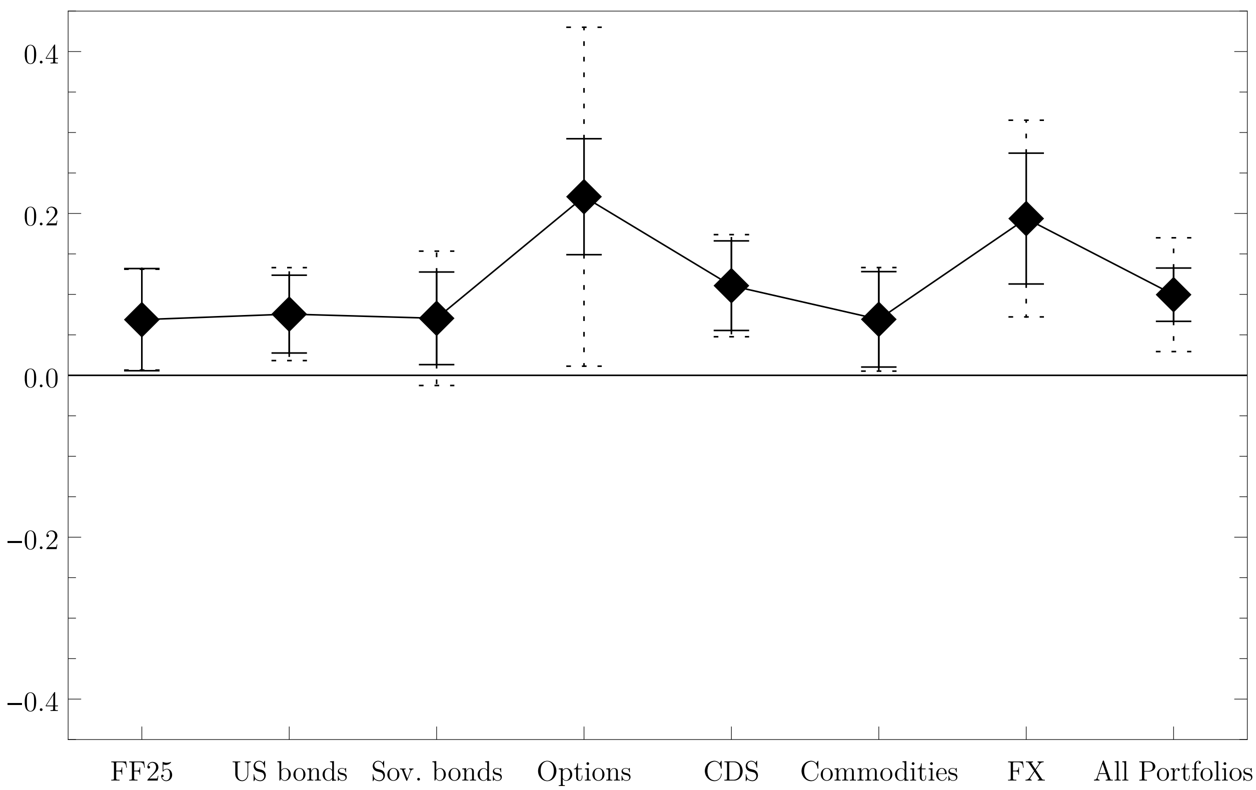
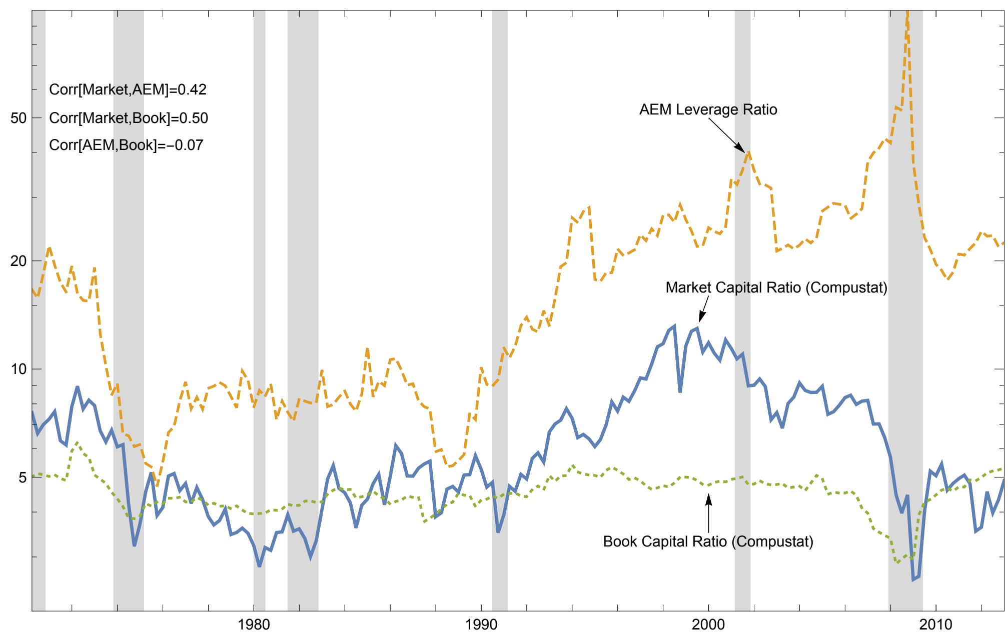
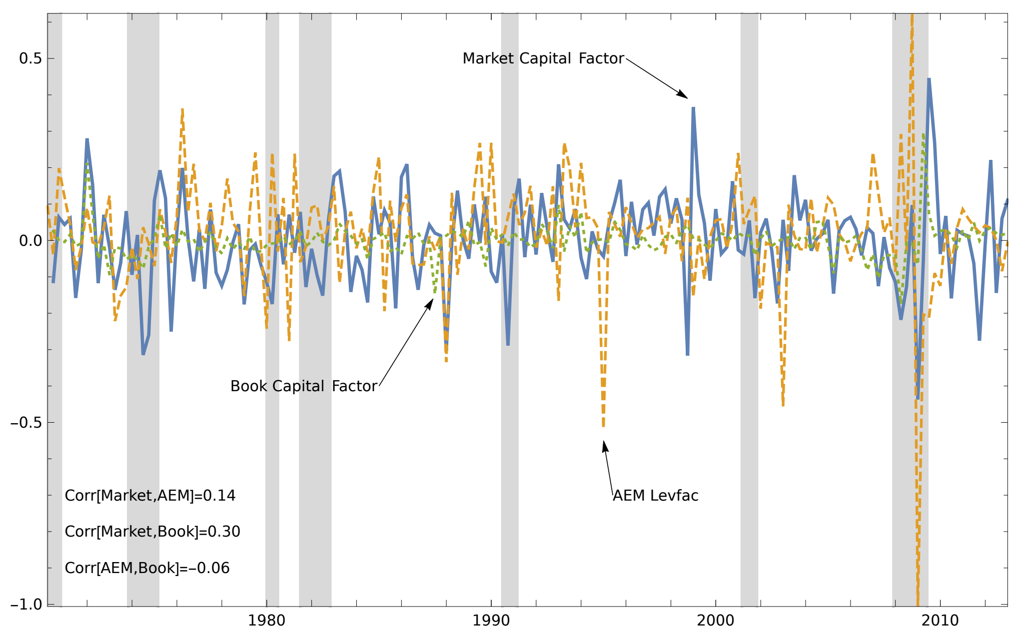


Figure 2: **Intermediary Capital Risk Price λ_η Estimates by Asset Class**
Risk price estimates for shocks to the intermediary capital ratio, from a two-factor model that includes the excess return on the market. Risk prices are the mean slopes of period-by-period cross-sectional regressions of portfolio excess returns on risk exposures (betas). 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Solid error bars are the 95% confidence interval around the point estimates, calculated using Fama-MacBeth standard errors that adjust for cross-asset correlation in the residuals. Dotted error bars use the more robust GMM standard errors that additionally correct for estimation error of the time-series betas.



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



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

Figure 3: **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 ratio is 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Shaded regions indicate NBER recessions.

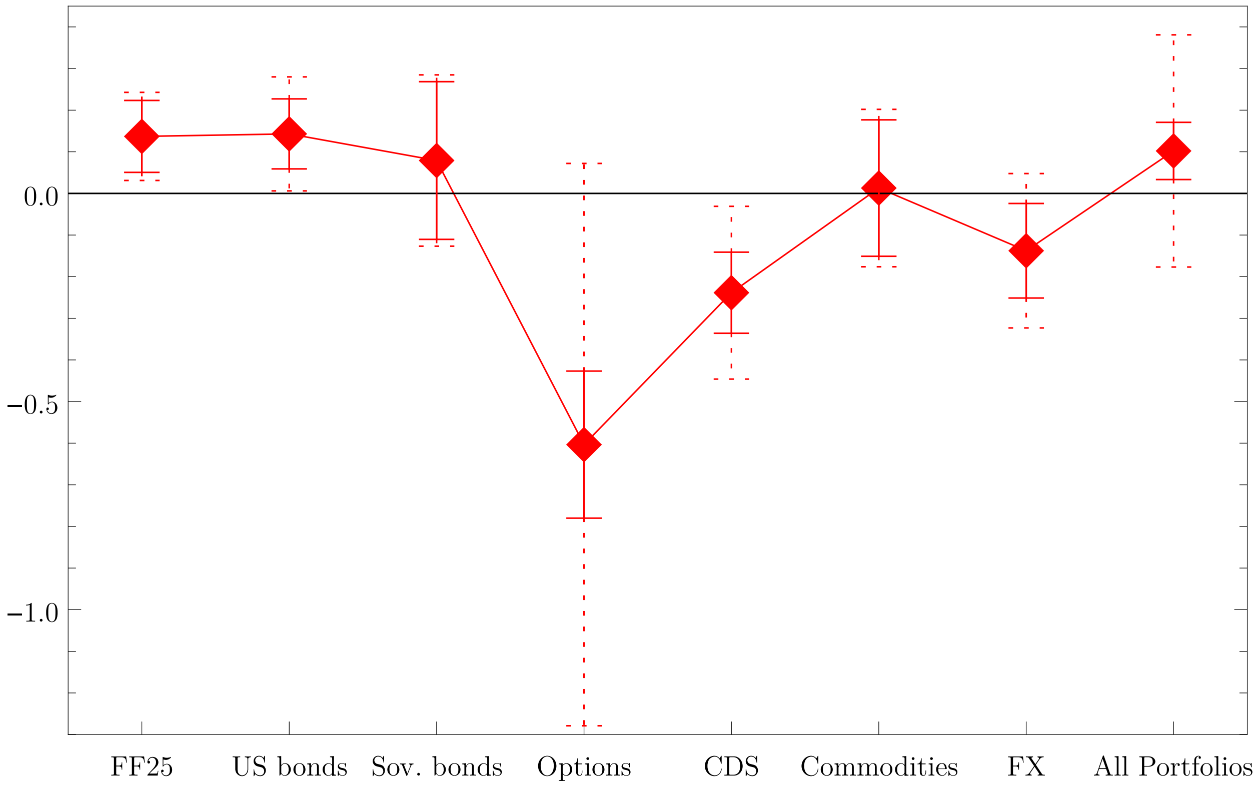


Figure 4: **AEM Leverage Factor**

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). 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Solid error bars are the 95% confidence interval around the point estimates, calculated using Fama-MacBeth standard errors that adjust for cross-asset correlation in the residuals. Dotted error bars use the more robust GMM standard errors that additionally correct 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 New York 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
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 from its authors which is defined as the seasonally adjusted growth rate in broker-dealer book leverage from Flow of Funds. Correlation for factors are with 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 Ptfs.
Mean($\mu_i - r_f$)	0.02	0.01	0.02	0.01	0.00	0.02	-0.01	0.01
Std($\mu_i - r_f$)	0.01	0.00	0.01	0.02	0.01	0.03	0.01	0.02
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	0.32	0.03	0.15
Mean($\beta_{i,W}$)	1.01	0.06	0.09	0.84	0.04	0.60	0.15	0.56
Std($\beta_{i,W}$)	0.30	0.07	0.12	0.11	0.03	0.34	0.04	0.42
Mean(R^2)	0.78	0.09	0.30	0.78	0.63	0.15	0.03	0.50
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	135	172

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

Average 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. The AEM leverage factor, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Betas are estimated in a first-stage time-series regression.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
Capital	0.07	0.08	0.07	0.22	0.11	0.07	0.19	0.10
t-FM	(2.14)	(3.08)	(2.41)	(6.04)	(3.92)	(2.30)	(4.70)	(5.93)
t-GMM	(2.16)	(2.58)	(1.66)	(2.07)	(3.44)	(2.12)	(3.12)	(2.78)
Market	0.01	0.01	0.01	0.03	0.01	0.03	0.10	0.02
t-FM	(0.81)	(1.13)	(0.49)	(1.99)	(0.64)	(1.46)	(3.38)	(2.08)
t-GMM	(0.78)	(0.82)	(0.32)	(0.84)	(0.41)	(1.29)	(2.17)	(1.00)
Intercept	0.00	0.00	0.00	-0.01	-0.00	0.01	-0.01	-0.00
t-FM	(0.34)	(1.99)	(0.56)	(-1.29)	(-5.69)	(0.85)	(-1.77)	(-0.64)
t-GMM	(0.33)	(1.33)	(0.33)	(-0.47)	(-2.77)	(0.72)	(-0.84)	(-0.49)
R^2	0.53	0.84	0.81	0.93	0.67	0.44	0.53	0.49
MAPE, %	0.34	0.13	0.32	0.30	0.18	1.84	0.44	0.86
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	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). 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. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
Capital	0.16	0.12	0.43	-0.79	0.67	-0.01	-0.03	0.03
t-FM	(2.62)	(0.91)	(1.81)	(-7.04)	(5.22)	(-0.05)	(-0.17)	(0.57)
t-GMM	(2.45)	(0.69)	(1.24)	(-3.34)	(2.55)	(-0.04)	(-0.12)	(0.22)
Market	-0.02	0.04	0.06	-0.05	0.07	0.05	0.12	0.02
t-FM	(-1.92)	(3.24)	(2.61)	(-3.10)	(3.62)	(2.18)	(3.45)	(2.24)
t-GMM	(-1.66)	(2.51)	(1.74)	(-1.86)	(2.99)	(1.81)	(2.45)	(1.03)
Intercept	0.04	0.00	0.00	0.06	-0.00	-0.00	-0.02	-0.00
t-FM	(3.82)	(1.87)	(0.43)	(4.55)	(-5.87)	(-0.20)	(-4.58)	(-0.15)
t-GMM	(3.37)	(1.71)	(0.22)	(2.19)	(-2.72)	(-0.19)	(-2.13)	(-0.17)
R^2	0.54	0.82	0.81	0.95	0.86	0.38	0.50	0.44
MAPE, %	0.36	0.14	0.32	0.26	0.15	1.92	0.45	1.07
Assets	25	20	6	54	20	24	12	161
Quarters	165	148	65	103	47	42	135	172

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

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
Capital	-0.01	0.03	0.02	-0.00	0.00	0.02	0.07	0.00
t-FM	(-0.70)	(3.76)	(2.21)	(-0.38)	(0.34)	(2.13)	(5.17)	(0.45)
t-GMM	(-0.70)	(2.90)	(1.42)	(-0.21)	(0.15)	(1.83)	(2.16)	(0.43)
Market	-0.01	0.03	0.02	0.05	0.09	0.05	0.14	0.02
t-FM	(-0.85)	(2.51)	(1.00)	(3.17)	(4.32)	(2.16)	(5.42)	(2.24)
t-GMM	(-0.83)	(1.72)	(0.88)	(1.69)	(1.78)	(1.87)	(2.78)	(1.11)
Intercept	0.03	0.00	0.02	-0.04	-0.00	-0.00	-0.02	-0.00
t-FM	(3.14)	(2.67)	(1.59)	(-3.72)	(-4.13)	(-0.02)	(-4.53)	(-0.57)
t-GMM	(3.05)	(1.52)	(1.57)	(-1.72)	(-1.38)	(-0.02)	(-1.57)	(-0.52)
R^2	0.08	0.85	0.74	0.88	0.90	0.38	0.51	0.38
MAPE, %	0.54	0.12	0.46	0.38	0.13	1.93	0.46	1.14
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	135	172

(b) **Non-Banks**

Table 6: **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). 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Mean absolute pricing error (MAPE) is in percentage terms. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
ME	0.07	0.05	0.05	0.06	0.06	0.07	0.19	0.10
t-FM	(2.03)	(2.18)	(1.38)	(2.25)	(1.87)	(2.24)	(5.66)	(5.27)
t-GMM	(1.62)	(1.34)	(0.86)	(0.72)	(1.32)	(2.06)	(4.30)	(2.25)
BD	-0.02	0.04	-0.07	-0.11	-0.10	-0.01	-0.00	-0.02
t-FM	(-2.02)	(2.46)	(-2.93)	(-5.65)	(-4.54)	(-0.30)	(-0.13)	(-2.01)
t-GMM	(-1.51)	(1.53)	(-2.24)	(-1.32)	(-2.12)	(-0.28)	(-0.08)	(-0.65)
Market	0.01	0.05	0.02	-0.01	-0.01	0.03	0.09	0.02
t-FM	(0.57)	(3.78)	(0.89)	(-0.39)	(-0.28)	(1.36)	(3.44)	(1.88)
t-GMM	(0.46)	(2.01)	(0.48)	(-0.11)	(-0.17)	(1.22)	(2.12)	(0.83)
Intercept	0.01	0.00	-0.00	0.01	-0.00	0.01	-0.01	-0.00
t-FM	(0.73)	(0.92)	(-0.24)	(1.02)	(-5.78)	(1.24)	(-1.46)	(-0.33)
t-GMM	(0.56)	(0.67)	(-0.12)	(0.25)	(-3.25)	(1.15)	(-0.78)	(-0.28)
R^2	0.51	0.89	0.90	0.96	0.86	0.45	0.54	0.51
MAPE, %	0.35	0.09	0.29	0.22	0.15	1.84	0.44	0.90
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	135	172

Table 7: **Market Equity is More Important for Pricing than Book Debt**

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). 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. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
AEM	0.14	0.14	0.08	-0.60	-0.24	0.01	-0.14	0.10
t-FM	(3.11)	(3.33)	(0.82)	(-6.69)	(-4.80)	(0.15)	(-2.38)	(2.91)
t-GMM	(2.54)	(2.05)	(0.75)	(-1.75)	(-2.25)	(0.13)	(-1.46)	(0.72)
Market	0.01	0.04	0.03	0.01	0.05	0.05	0.09	0.02
t-FM	(0.66)	(3.67)	(1.54)	(0.91)	(2.52)	(2.08)	(4.08)	(2.34)
t-GMM	(0.57)	(1.77)	(1.00)	(0.21)	(2.24)	(1.90)	(2.62)	(1.14)
Intercept	0.01	0.00	0.01	-0.02	-0.00	-0.00	-0.02	-0.00
t-FM	(0.65)	(0.97)	(1.64)	(-1.50)	(-2.48)	(-0.05)	(-4.45)	(-0.85)
t-GMM	(0.52)	(0.52)	(1.65)	(-0.27)	(-1.15)	(-0.04)	(-2.23)	(-0.50)
R^2	0.70	0.87	0.73	0.95	0.93	0.38	0.59	0.39
MAPE, %	0.27	0.12	0.45	0.24	0.11	1.93	0.36	0.98
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	135	172

Table 8: **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). Betas are estimated in a first-stage time-series regression. The quarterly sample is 1970Q1–2012Q4. The AEM leverage factor, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Mean absolute pricing error (MAPE) is in percentage terms. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
Mean($\mu_i - r_f$)	0.02	0.01	0.02	0.01	0.00	0.02	-0.01	0.01
Std($\mu_i - r_f$)	0.01	0.00	0.01	0.02	0.01	0.03	0.01	0.02
Mean($\beta_{i,AEM}$)	0.03	0.01	-0.01	-0.02	0.00	0.05	-0.02	0.00
Std($\beta_{i,AEM}$)	0.05	0.01	0.04	0.02	0.01	0.08	0.02	0.05
Mean($\beta_{i,W}$)	1.08	0.09	0.34	0.83	0.11	0.47	0.06	0.56
Std($\beta_{i,W}$)	0.20	0.10	0.22	0.17	0.07	0.39	0.05	0.43
Mean(R^2)	0.77	0.09	0.23	0.78	0.52	0.13	0.02	0.49
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	135	172

Table 9: **Expected Returns and Risk Exposure by Asset Class: AEM Leverage Factor** Average 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Betas are estimated in a first-stage time-series regression.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
Capital	-0.02	0.08	0.11	0.09	0.06	0.07	0.14	0.10
t-FM	(-0.48)	(3.14)	(3.13)	(2.76)	(2.17)	(2.30)	(4.54)	(5.90)
t-GMM	(-0.32)	(3.32)	(2.95)	(0.73)	(2.59)	(2.13)	(2.92)	(2.82)
Market	0.01	0.02	0.00	0.01	0.02	0.03	0.07	0.02
t-FM	(0.40)	(1.99)	(0.15)	(0.33)	(1.27)	(1.34)	(2.91)	(1.87)
t-GMM	(0.29)	(0.73)	(0.07)	(0.12)	(1.01)	(1.32)	(1.90)	(0.89)
AEM	0.18	0.13	-0.12	-0.42	-0.21	0.03	-0.12	-0.00
t-FM	(3.91)	(3.19)	(-1.17)	(-7.16)	(-4.39)	(0.35)	(-2.15)	(-0.11)
t-GMM	(2.23)	(1.88)	(-0.56)	(-2.12)	(-3.24)	(0.29)	(-1.38)	(-0.03)
Intercept	0.01	0.00	-0.01	-0.00	-0.00	0.01	-0.01	-0.00
t-FM	(0.88)	(1.02)	(-0.94)	(-0.39)	(-2.99)	(0.85)	(-2.10)	(-0.40)
t-GMM	(0.61)	(0.51)	(-0.78)	(-0.12)	(-1.94)	(0.73)	(-1.02)	(-0.35)
R^2	0.71	0.88	0.85	0.97	0.94	0.44	0.62	0.50
MAPE, %	0.27	0.11	0.29	0.17	0.09	1.83	0.38	0.88
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	135	172

Table 10: **Horse-races with the AEM Leverage Factor**

Risk price estimates for shocks to the intermediary capital ratio (Capital), 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). 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Mean absolute pricing error (MAPE) is in percentage terms. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.12	0.14	0.02	0.02	-0.00	-0.03	0.20	-0.31
t-FM	(2.66)	(3.20)	(0.42)	(0.38)	(-0.05)	(-0.72)	(6.65)	(-6.24)
t-GMM	(1.84)	(2.22)	(0.33)	(0.31)	(-0.05)	(-0.56)	(1.99)	(-3.17)
Market	0.03	0.01	0.05	0.04	0.07	0.05	-0.01	0.06
t-FM	(1.58)	(0.94)	(3.55)	(3.08)	(3.05)	(2.28)	(-0.50)	(3.34)
t-GMM	(1.14)	(0.72)	(2.56)	(2.79)	(2.54)	(2.05)	(-0.16)	(1.45)
Intercept	-0.01	0.00	0.00	0.00	0.02	0.01	0.02	-0.05
t-FM	(-0.82)	(0.26)	(3.11)	(3.24)	(2.47)	(0.86)	(1.24)	(-3.28)
t-GMM	(-0.60)	(0.18)	(3.05)	(2.84)	(1.98)	(0.80)	(0.37)	(-1.46)
R^2	0.70	0.72	0.86	0.83	0.71	0.54	0.94	0.89
MAPE, %	0.34	0.30	0.11	0.10	0.53	0.67	0.30	0.33
Assets	25	25	20	20	6	6	54	54
Quarters	148	148	128	128	48	48	83	83

	CDS		Commod.		FX		All Ptfs.	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.08	-0.16	0.03	-0.01	0.16	-0.03	0.10	0.08
t-FM	(2.62)	(-3.55)	(0.97)	(-0.27)	(4.00)	(-0.57)	(5.37)	(2.62)
t-GMM	(1.88)	(-2.50)	(0.91)	(-0.26)	(2.82)	(-0.34)	(4.13)	(1.84)
Market	0.07	0.06	0.02	0.03	0.10	0.11	0.02	0.02
t-FM	(3.27)	(2.31)	(0.93)	(1.06)	(3.19)	(5.02)	(1.92)	(2.21)
t-GMM	(3.23)	(1.50)	(0.81)	(0.91)	(1.98)	(2.94)	(1.00)	(1.08)
Intercept	-0.00	-0.00	0.04	0.04	-0.00	-0.01	-0.00	-0.00
t-FM	(-2.22)	(-1.77)	(3.65)	(3.05)	(-0.91)	(-3.44)	(-0.37)	(-0.69)
t-GMM	(-1.55)	(-0.88)	(3.77)	(2.96)	(-0.47)	(-1.74)	(-0.63)	(-0.58)
R^2	0.84	0.95	0.13	0.12	0.55	0.52	0.10	0.10
MAPE, %	0.12	0.08	2.90	2.87	0.38	0.41	1.45	1.38
Assets	20	20	24	24	12	12	161	161
Quarters	23	23	19	19	123	123	148	148

Table 11: **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). 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Mean absolute pricing error (MAPE) is in percentage terms. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.02	0.09	0.04	0.00	0.07	0.08	0.29	-0.55
t-FM	(0.70)	(1.39)	(1.20)	(0.06)	(2.36)	(0.82)	(5.73)	(-7.04)
t-GMM	(0.75)	(1.34)	(1.21)	(0.05)	(1.58)	(0.75)	(1.51)	(-2.10)
Market	-0.00	0.00	0.03	0.03	0.01	0.03	0.02	0.02
t-FM	(-0.03)	(0.11)	(2.24)	(2.28)	(0.50)	(1.54)	(1.05)	(1.23)
t-GMM	(-0.03)	(0.11)	(2.01)	(2.07)	(0.33)	(1.00)	(0.35)	(0.31)
Intercept	0.02	0.02	0.01	0.01	0.00	0.01	-0.00	-0.02
t-FM	(1.26)	(1.25)	(4.38)	(3.87)	(0.56)	(1.64)	(-0.38)	(-1.65)
t-GMM	(1.33)	(1.26)	(4.15)	(3.59)	(0.32)	(1.65)	(-0.10)	(-0.31)
R^2	0.28	0.30	0.64	0.64	0.80	0.73	0.88	0.92
MAPE, %	0.42	0.41	0.22	0.22	0.33	0.45	0.37	0.32
Assets	25	25	20	20	6	6	54	54
Quarters	92	92	88	88	65	65	88	88
	CDS		**Commod.**		**FX**		**All Ptfs.**	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.10	-0.24	0.07	0.01	0.07	-0.14	0.07	0.04
t-FM	(3.62)	(-4.80)	(2.26)	(0.15)	(2.35)	(-2.90)	(3.73)	(0.87)
t-GMM	(3.75)	(-2.25)	(2.09)	(0.13)	(2.15)	(-2.24)	(2.12)	(0.36)
Market	0.03	0.05	0.03	0.05	0.05	0.03	0.02	0.02
t-FM	(1.51)	(2.52)	(1.54)	(2.08)	(1.83)	(1.35)	(1.63)	(2.09)
t-GMM	(1.20)	(2.24)	(1.37)	(1.90)	(1.65)	(1.18)	(0.95)	(1.19)
Intercept	-0.00	-0.00	0.01	-0.00	-0.01	-0.01	-0.00	-0.00
t-FM	(-5.62)	(-2.48)	(0.71)	(-0.05)	(-1.43)	(-1.62)	(-0.41)	(-1.20)
t-GMM	(-3.14)	(-1.15)	(0.59)	(-0.04)	(-1.09)	(-1.14)	(-0.20)	(-0.62)
R^2	0.64	0.93	0.42	0.38	0.18	0.43	0.40	0.31
MAPE, %	0.19	0.11	1.86	1.93	0.48	0.39	0.96	1.05
Assets	20	20	24	24	12	12	161	161
Quarters	47	47	42	42	80	80	92	92

Table 12: **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). 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Mean absolute pricing error (MAPE) is in percentage terms. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
Capital	0.01	0.01	0.02	0.07	0.06	0.03	0.07	0.04
t-FM	(1.20)	(0.77)	(1.65)	(2.74)	(5.32)	(2.36)	(4.64)	(6.12)
t-GMM	(1.16)	(0.71)	(1.35)	(1.30)	(3.09)	(2.25)	(3.51)	(3.19)
Market	0.00	0.01	0.02	0.03	-0.00	0.01	0.03	0.01
t-FM	(0.17)	(1.90)	(2.72)	(5.09)	(-0.23)	(1.71)	(2.57)	(3.46)
t-GMM	(0.17)	(1.71)	(2.16)	(2.85)	(-0.16)	(1.62)	(1.76)	(1.48)
Intercept	0.01	0.00	0.00	-0.03	-0.00	0.00	-0.00	-0.00
t-FM	(1.68)	(4.34)	(0.09)	(-4.71)	(-6.85)	(0.54)	(-2.28)	(-2.99)
t-GMM	(1.65)	(4.11)	(0.06)	(-2.54)	(-3.90)	(0.47)	(-1.33)	(-1.91)
R^2	0.27	0.78	0.71	0.83	0.72	0.37	0.32	0.37
MAPE, %	0.16	0.05	0.17	0.15	0.07	0.60	0.16	0.34
Assets	25	20	6	54	20	24	12	161
Quarters	516	449	196	310	143	128	407	516

Table 13: **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). Betas are estimated in a first-stage time-series regression. The AEM leverage factor, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Mean absolute pricing error (MAPE) is in percentage terms. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct 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	-2.90
t-Hodrick	(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	0.17
Assets	25	25	20	20	6	6	54	54
Quarters	168	168	145	145	62	62	100	100
	CDS		Commod.		FX		All Ptfs.	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Leverage	0.14	-1.30	-0.01	-1.97	-0.10	0.65	0.10	-2.16
t-Hodrick	(3.20)	(-0.49)	(-0.46)	(-1.98)	(-2.15)	(0.70)	(2.92)	(-2.15)
R^2	0.21	0.04	0.01	0.26	0.10	0.01	0.13	0.12
Assets	20	20	24	24	12	12	161	161
Quarters	44	44	39	39	132	132	169	169

Table 14: **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	0.00	0.14	0.05	0.25	0.06	0.19	0.13	-1.06
t-FM	(0.02)	(3.26)	(3.16)	(4.48)	(2.37)	(2.19)	(5.12)	(-5.84)
t-GMM	(0.02)	(2.60)	(3.05)	(1.25)	(1.83)	(0.67)	(3.18)	(-0.41)
Intercept	0.02	0.00	0.00	0.00	0.00	0.02	-0.05	0.03
t-FM	(1.61)	(0.38)	(1.99)	(1.50)	(0.73)	(3.04)	(-4.71)	(3.07)
t-GMM	(1.61)	(0.23)	(1.74)	(0.70)	(0.51)	(1.08)	(-2.88)	(0.27)
R^2	0.00	0.69	0.83	0.21	0.77	0.57	0.89	0.86
MAPE, %	0.55	0.27	0.13	0.29	0.42	0.55	0.37	0.45
Assets	25	25	20	20	6	6	54	54
Quarters	172	172	148	148	65	65	103	103

	CDS		Commod.		FX		All Ptfs.	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.08	-0.26	0.07	0.11	0.19	-0.26	0.04	0.15
t-FM	(3.24)	(-5.14)	(2.28)	(1.42)	(4.55)	(-3.59)	(2.53)	(3.67)
t-GMM	(3.25)	(-2.84)	(2.04)	(0.89)	(3.28)	(-2.27)	(1.25)	(0.61)
Intercept	-0.00	0.00	0.01	0.01	-0.01	-0.01	-0.00	0.00
t-FM	(-5.72)	(2.52)	(0.53)	(1.18)	(-2.67)	(-3.93)	(-0.58)	(0.32)
t-GMM	(-3.71)	(1.06)	(0.40)	(0.93)	(-1.13)	(-1.58)	(-0.55)	(0.05)
R^2	0.64	0.35	0.43	0.11	0.53	0.37	0.44	0.18
MAPE, %	0.20	0.33	1.85	2.15	0.44	0.49	0.96	1.08
Assets	20	20	24	24	12	12	161	161
Quarters	47	47	42	42	135	135	172	172

(a) **Capital Ratio or AEM Leverage**

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All Ptfs.
Capital	-0.00	0.05	0.06	0.14	0.09	0.07	0.19	0.04
t-FM	(-0.14)	(3.17)	(2.32)	(5.09)	(3.24)	(2.22)	(4.66)	(2.48)
t-GMM	(-0.14)	(3.10)	(1.77)	(3.05)	(2.91)	(1.95)	(3.44)	(1.20)
Intercept	0.02	0.00	0.00	-0.05	-0.00	0.00	-0.01	-0.00
t-FM	(1.77)	(1.72)	(0.69)	(-4.81)	(-5.74)	(0.31)	(-3.12)	(-0.58)
t-GMM	(1.76)	(1.55)	(0.48)	(-2.80)	(-3.73)	(0.24)	(-1.41)	(-0.59)
R^2	0.00	0.84	0.72	0.87	0.63	0.42	0.58	0.43
MAPE, %	0.56	0.13	0.46	0.40	0.20	1.88	0.42	0.96
Assets	25	20	6	54	20	24	12	161
Quarters	172	148	65	103	47	42	135	172

(b) **Intermediary Equity Return**

Table 15: **Single Factor Models**

Panel (a) reports risk price estimates for shocks to the intermediary capital ratio (HKM) or the Adrian et al. (2014a) leverage factor (AEM) alone. The capital factor considered in Panel (b) is the value-weighted equity return of primary dealers. 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors.

	FF25		US bonds		Sov. bonds		Options	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.08	0.15	0.10	0.25	0.08	-0.02	0.25	-0.78
t-FM	(4.34)	(4.11)	(3.42)	(2.61)	(3.41)	(-0.23)	(5.55)	(-5.60)
t-GMM	(3.76)	(3.38)	(2.29)	(1.05)	(3.49)	(-0.18)	(1.43)	(-0.65)
Market	0.02	0.02	0.03	0.05	0.01	0.05	0.01	-0.01
t-FM	(2.14)	(2.08)	(2.03)	(3.51)	(0.55)	(2.98)	(1.55)	(-1.03)
t-GMM	(2.04)	(2.04)	(1.36)	(1.98)	(0.33)	(2.47)	(1.04)	(-0.25)
R^2	0.53	0.70	0.84	0.87	0.81	0.73	0.93	0.95
MAPE, %	0.34	0.27	0.23	0.12	0.34	0.51	0.31	0.28
Assets	25	25	20	20	6	6	54	54
Quarters	172	172	148	148	65	65	103	103
	CDS		**Commod.**		**FX**		**All Ptfs.**	
	HKM	AEM	HKM	AEM	HKM	AEM	HKM	AEM
Capital	0.07	-0.26	0.07	0.01	0.24	0.01	0.10	0.10
t-FM	(2.61)	(-5.29)	(2.47)	(0.13)	(5.23)	(0.21)	(6.48)	(2.95)
t-GMM	(2.58)	(-2.54)	(2.19)	(0.11)	(2.58)	(0.18)	(2.82)	(0.70)
Market	0.00	0.04	0.04	0.05	0.07	-0.06	0.02	0.02
t-FM	(0.19)	(2.11)	(1.98)	(2.27)	(2.56)	(-1.90)	(2.12)	(2.30)
t-GMM	(0.15)	(1.86)	(1.46)	(2.06)	(1.17)	(-1.49)	(0.88)	(0.89)
R^2	0.67	0.93	0.44	0.38	0.53	0.59	0.49	0.39
MAPE, %	0.26	0.12	1.92	1.92	0.50	1.03	0.88	1.00
Assets	20	20	24	24	12	12	161	161
Quarters	47	47	42	42	135	135	172	172

Table 16: **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). 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, defined as the seasonally adjusted growth rate in broker-dealer book leverage level from Flow of Funds, is from its authors. Mean absolute pricing error (MAPE) is in percentage terms. Fama-MacBeth t-statistics (t-FM) adjust for cross-asset correlation in the residuals. The more robust GMM t-statistics (t-GMM) additionally correct for estimation error of the time-series betas.

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.