Heterogeneous Intermediary Capital and the Cross-Section of Stock Returns[*]

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Abstract

This paper examines how heterogeneity in intermediary capital – the equity capital ratio of the largest financial intermediaries in the U.S. – affects the cross-section of stock returns. I estimate the exposure (i.e., beta) of individual stocks to a shock in the dispersion of intermediary capital and find that stocks in the lowest beta decile generate an additional 6.8% - 8.2% annual return relative to stocks in the highest beta decile. Using data from Institutional (13F) Holdings, I also find evidence that low-capital intermediaries, who hold riskier assets than high-capital intermediaries, face leverage-induced fire sales during bad times. I propose a model of heterogeneous intermediary capital in which heterogeneous risk preference between high- and low-capital intermediaries leads to a countercyclical variation in aggregate risk aversion and a risk premium. The model states that the dispersion of intermediary capital is priced in the cross-section of asset prices, which supports the empirical findings.

Keywords: Intermediary Capital, Heterogeneous Agents, Risk Aversion, Fire Sales

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1 Introduction

The role of financial intermediation has been emphasized in recent literatures to understand business cycles and financial markets. In particular, the financial crisis in the late 2000's has highlighted that frictions in financial intermediation help to explain the movement of asset prices, which in turn has led to the growing popularity of "intermediary asset pricing". Different from the traditional perspective of consumption-based asset pricing models,[1] intermediary asset pricing models argue that financial intermediaries are the marginal investors who can trade across various sophisticated asset classes and account for a major portion of trades. As intermediary capital affects their trading decisions, a stochastic discount factor should include the time variation in intermediary capital (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014).

Financial intermediaries have different levels of capital in the cross-section. Intuitively, low-capital intermediaries will have higher (lower) return on capital than high-capital intermediaries during good (bad) times due to leverage, implying that the time variation in capital of high- and low-capital intermediaries will be different. Heterogeneous agent models highlight that the cross-sectional difference of marginal investors in various aspects is important in asset pricing. For example, a risk premium can be driven by the cross-sectional distribution of agents' income and consumption (Constantinides and Duffie, 1996) or risk preference (Chan and Kogan, 2002; Gârleanu and Panageas, 2015). Existing studies in an intermediary asset pricing literature ignore heterogeneity in intermediary capital, though it seems important to examine heterogeneity of marginal investors under the framework of intermediary asset pricing models. This leads to the following research question: Can the dynamics of the heterogeneity in intermediary capital play an important role in determining a stochastic discount factor?

In this paper, I study the cross-sectional distribution of intermediary capital and its effect on asset pricing. My first empirical analysis focuses on how heterogeneity in intermediary capital affects the cross-section of stock returns. I measure the heterogeneity in intermediary capital as dispersion of capital ratios, that is, the difference between the 75^{th} and the 25^{th} percentile of the

[1] The limitation of consumption-based asset pricing models has been reviewed extensively in prior studies. For example, household consumers are lazy in making consumption and investment decisions (Jagannathan and Wang, 2007), they rebalance portfolios very infrequently (Brunnermeier and Nagel, 2008), or information-averse households are inattentive to savings (Andries and Haddad, 2018).

quasi-market capital ratio of the largest 30 intermediaries in the U.S.,[2] scaled by its 50^{th} percentile. Note that the dispersion of capital ratios increases (decreases) when low-capital intermediaries lose (earn) more than high-capital intermediaries during bad (good) times. Consistently, I find that it is highly countercyclical. Next, using all stocks listed on NYSE, AMEX, or NASDAQ, I estimate each stock's exposure to a shock in the dispersion of capital ratios (i.e., β^{DISP}). I find strong evidence that the dispersion of capital ratios is *negatively* priced in the cross-section of stock returns. Stocks in the lowest dispersion beta decile generate an additional 6.8% - 8.2% annual risk premium relative stocks in the highest dispersion beta decile, after controlling for various risk factors including the level of intermediary capital.

The results are consistent with Chan and Kogan (2002) and Gârleanu and Panageas (2015) who argue that when agents are heterogeneous in risk aversion, aggregate risk aversion exhibits a countercyclical variation due to compositional changes in aggregate wealth. Importantly, the fraction of capital controlled by high- (low-) capital intermediaries rises (falls) in economic downturns.[3] Given that more risk-tolerant intermediaries use higher leverage (equivalently, maintain lower capital),[4] the aggregate risk aversion increases (decreases) in bad (good) times. This implies that risk captured by the dispersion beta is each stock's exposure to a shock in the aggregate risk aversion. Therefore, stocks with the high dispersion beta exhibit a lower risk premium, providing a hedge against the heightened risk aversion, and stocks with the low dispersion beta are riskier and therefore earn a higher premium.

To rationalize this conjecture, I propose a model of heterogeneous intermediary capital in an economy populated with two specialists and one household. A key feature of the model is that specialists have a power utility function with internal habits but exhibit heterogeneity in habit persistence, which leads to heterogeneous risk aversion of specialists. The constraint in raising capital allows a more risk-averse specialist to attract more equity capital from the household to form an intermediary, a feature consistent with the positive relation (documented in this paper)

[2] The financial intermediaries comprise commercial banks, investment banks, mutual funds, hedge funds, broker-dealers, or their holdings companies. Participation of these intermediaries in stock markets is sizable. Based on my sample, their stock holdings in the U.S. are over $3.3 trillion, and the average ratio of stock holdings over book assets is 26.0% in 2012.

[3] In this light, the dispersion of capital ratios is defined to essentially measure the difference between the fractions of capital controlled by high- and low-capital intermediaries.

[4] This implies a positive association between intermediary capital and risk aversion. In Section 2, I discuss the relation in detail.

between capital of intermediaries and their risk aversion.

In addition, it is likely that low-capital intermediaries would face scarce funding liquidity in bad times, incurring a hike in margin requirements (liquidity spirals as in Brunnermeier and Pedersen, 2009). More importantly, if the shock is systematic, all low-capital intermediaries may be forced to deleverage by selling off assets, and this may lead leverage-induced fire sales (Bian, He, Shue, and Zhou, 2018). In contrast, high-capital intermediaries who have sufficient capital can potentially absorb these asset sales, as argued in Acharya and Viswanathan (2011). Given that high-capital intermediaries have higher risk aversion than low-capital intermediaries, they will not buy those assets unless the prices drop sufficiently. This further triggers fire sales during bad times. As a result, low- (high-) capital intermediaries may sell (buy) assets at prices lower than fundamental values, implying that the net worth of low-capital intermediaries would transfer to high-capital intermediaries during bad times.

Next, I perform tests to analyze the trading activity of financial intermediaries by using the Thomson Reuters Institutional (13F) Holdings database. At each quarter end, I manually match managers in the Institutional (13F) Holdings database with their holding companies in the Compustat Quarterly database. The matched data allow me to directly examine how different capital ratios of financial intermediaries affect their holdings of nonfinancial firm stocks and trades, especially during bad times (i.e., when the dispersion of capital ratios is high). I document the following results.

First, low-capital intermediaries sell substantial amounts of stocks during bad times while high-capital intermediaries do not. However, by tracking the types of stocks bought and sold by financial intermediaries, I show that high-capital intermediaries purchase significantly more stocks that low-capital intermediaries sell, and low-capital intermediaries sell significantly more stocks that high-capital intermediaries purchase during such times. This is consistent with the notion that there are asset transfers from low-capital intermediaries to high-capital intermediaries during bad times.

Second, to test whether the stocks sold by low-capital intermediaries are indeed fire-sold, I examine trading gains of financial intermediaries during bad times. Since the Thomson Reuters Institutional (13F) Holdings database provides neither the exact transaction date nor the parties involved in the transaction, I am only able to infer fire sales by observing trading gains (i.e., abnormal returns) of financial intermediaries in the following quarter. I find that high-capital intermediaries earn positive trading gains on stock purchases while low-capital intermediaries lose in terms of forgone returns on stock sales in the following quarter. That is, consistent with a fire sales interpretation, stocks are sold at prices lower than fundamental values.

Finally, when they trade stocks, there is a "trade mismatch" between high- and low-capital intermediaries. To see this, note the following. High-capital intermediaries may be so risk-averse that they are only willing to buy assets that have fallen in price (i.e., stocks with low dispersion betas). At the same time, low-capital intermediaries may hesitate to sell those assets if they believe prices have temporarily dropped below their fundamental values and will recover again. They may therefore choose to sell stocks that have experienced a modest price drop (i.e., stocks with moderate dispersion betas). In support of this argument, I show that during bad times, high-capital intermediaries tend to purchase more stocks with low dispersion betas whereas low-capital intermediaries are likely to sell more stocks with medium dispersion betas.

My paper adds to the literature on intermediary asset pricing. After the theoretical ground established (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014), Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) test empirically that the level of intermediary capital (equivalently, the inverse of intermediary leverage) prices the cross-section of asset returns, including returns on equity portfolios. I provide the empirical evidence supporting the importance of the dispersion of intermediary capital in predicting stock returns, controlling for the level of intermediary capital. In the theoretical perspective, the level of intermediary capital captures wealth from a given utility function while the dispersion of intermediary capital captures the shape (i.e., curvature) of the utility function of a representative agent through compositional changes among heterogeneous agents.

There are also other studies that emphasize the important role of heterogeneous intermediaries in asset markets. While my paper addresses the heterogeneity in risk preference of intermediaries, financial intermediaries are modeled to be heterogeneous in terms of Value-at-Risk constraints in Coimbra and Rey (2018) or funding constraints in Ma (2018). These studies, including my work, feature the cross-sectional distribution of assets among intermediaries, which ultimately drives the risk premium. In the banking literature, the cross-sectional difference in bank capital has been shown to affect bank stock returns indirectly through the market beta (Baker and Wurgler, 2015) or conditionally during bad times (Bouwman, Kim, and Shin, 2018).

My work also complements the literature on heterogeneous agents and time-varying risk aversion. Chan and Kogan (2002) and Gârleanu and Panageas (2015) argue in their theoretical models that although agents' risk aversion is not time-varying, the aggregate risk aversion of the market can vary over time if agents are heterogeneous in risk aversion. Using intermediary capital as a proxy for risk aversion, I find empirical evidence that is consistent with their predictions; the aggregate risk aversion and the risk premium are countercyclical. Related, Brunnermeier and Nagel (2008) use micro-level data (i.e., Panel Study of Income Dynamics) to test how changes in risk aversion through a habit preference affect individuals' asset allocation. Gârleanu and Pedersen (2011) document that risk-tolerant agents operate with high leverage and that in bad times, a premium may rise once margin requirement starts to bind, reflecting scarce funding liquidity.

This paper is, to my best knowledge, the first attempt to directly investigate stock holdings of financial intermediaries in the U.S. By manually matching 13F managers with their holding companies, I am able to observe how financial intermediaries (and their subsidiaries) trade stocks, which enables me to analyze fire sales during bad times. While adverse selection prevents unconstrained investors from buying assets unless prices of those assets drop sufficiently in Dow and Han (2018), I argue that it is high risk-aversion that induces high-capital intermediaries buy assets only at discounted prices. This work is also consistent with Santos and Veronesi (2018), who argue in their model that levered agents fire-sell their risky assets to reduce leverage as asset prices decline during bad times. In addition, Bian, He, Shue, and Zhou (2018) empirically test leverage-induced fire sales in the Chinese stock market using proprietary account-level trading data for margin accounts in the middle of 2015 and find that investors whose leverage is close to the maximum level strongly sell their assets during the stock market crash.

The rest of the paper is organized as follows. Section 2 offers a discussion to provide a mechanism behind the role of heterogeneous intermediary capital in stock market. Section 3 explains data and sample. Section 4 presents the empirical tests and their results. Section 5 performs additional tests and robustness checks. Section 6 derives a model of heterogeneous intermediary capital in which the dispersion of intermediary capital is priced in the cross-section of stock returns. Section 7 concludes.

2 Heterogeneous Intermediary Capital

In this section, I discuss the role of the heterogeneous intermediary capital in explaining the cross-section of stock returns. Prior studies on intermediary asset pricing have focused on the level of intermediary capital. He and Krishnamurthy (2013) argue that intermediary capital represents the health of the intermediary sector: When an intermediary's constraint to raise capital is binding, intermediary capital becomes scarce, which leads to a higher risk premium. Based on this theoretical motivation, He, Kelly, and Manela (2017) find that intermediary capital, measured using market values, is positively priced in the cross-section of asset returns. In contrast, Adrian, Etula, and Muir (2014) use book leverage as a proxy for intermediary leverage to capture funding liquidity and find the positive price of risk for the leverage of financial intermediaries. Because intermediaries lower their leverage when funding constraints tighten (Brunnermeier and Pedersen, 2009), intermediary leverage, measured using book values, is procyclical as documented in Adrian and Shin (2010, 2014).

Since leverage is simply the inverse of the capital ratio, the two strands of studies seem to contradict each other.[5] However, as argued in Santos and Veronesi (2018), while deleveraging of low capital intermediaries in bad times causes book leverage to decrease, market leverage can increase if a high discount rate would push down the market value of capital faster than the decrease in debt. Therefore, the book capital ratio is expected to be procyclical, while the market capital ratio is to be countercyclical.

I argue that it is important to look beyond the level of intermediary capital: Intermediary capital appears to vary in the cross-section as well. From a principal component analysis of the quasi-market capital ratio based on the largest 30 intermediaries in the U.S., I find that the first two factors have eigenvalues greater than one. The first factor appears to represent the level of intermediary capital as standardized scores of the 25^{th} percentile and the 75^{th} percentile for the first factor are similar (i.e., 0.058 and 0.053, respectively). In contrast, the second seems to be the dispersion of intermediary capital as standardized scores of the 25^{th} percentile and the 75^{th} percentile for the second factor are in the opposite signs (i.e., -0.097 and 0.151, respectively). If

[5]Note that Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) use different definitions for financial intermediaries; the former defines intermediaries as security broker-dealers from the Federal Reserve *Flow of Funds*, and the latter defines intermediaries as *Primary Dealers* - Federal Reserve Bank of New York

the key features that drive this cross-sectional difference are associated with intermediaries' trading behaviors, it is potentially important to incorporate the heterogeneity in intermediary capital to examine the role of financial intermediaries in asset markets.

How does heterogeneous intermediary capital affect the trading behavior of intermediaries? As mentioned in the Introduction, I postulate that intermediary capital is closely related to the risk preference of intermediary and that intermediary capital appears to be positively associated with risk aversion of intermediaries. On the one hand, risk aversion may induce an intermediary to have high capital in that a risk-averse intermediary might want to build up precautionary capital against an adverse shock in economic downturns. On the other hand, capital can also reduce risk-taking behavior of intermediaries. For example, a low-capital intermediary with a limited liability has risk-shifting incentives and is likely to take an excessive risk at the expense of debt holders. According to the banking literature, as capital increases, banks' incentives to pursue high risk decline (Furlong and Keeley, 1989), and their incentives to monitor borrowers strengthen (Holmstrom and Tirole, 1997; Allen, Carletti, and Marquez, 2011).[6] Whether intermediary capital is indeed positively related to risk aversion could ultimately be an empirical question. Thus, as suggestive evidence, it is worthwhile investigating stock holdings of high- and low-capital intermediaries to empirically link their capital and risk preferences.

Figure 1 shows the relation between intermediary capital ratios and the risk characteristics of stocks owned by the largest 9 intermediaries in the U.S. that span at lease 30 quarters in the sample. It supports the channel in which intermediary capital is negatively associated with risk-taking behaviors (i.e., high risk aversion). It appears that high-capital intermediaries tend to hold stocks with lower market betas (in Panel A), lower return volatility (in Panel B), and larger market capitalization (in Panel C). Such differences are potentially more pronounced during bad times. For instance, in 2007, Lehman Brothers has a market capital ratio of 4.9% and holds stocks with a market beta of 2.70 on average whereas Bank of New York Mellon has a market capital ratio of 24.8% and holds stocks with a market beta of 0.79 on average. More generally, intermediaries holding stocks with distinctive risk characteristics played a critical role in the pricing of these stocks

[6] There is an opposite view that intermediary capital is negatively associated with risk aversion, arguing that intermediaries have more capital in equilibrium if they hold riskier assets in their balance sheets. To mitigate this concern, I measure intermediary capital based on marker values. A higher discount rate due to having riskier assets will discount their market capital. Thus, the effect of having extra book capital would be largely canceled out when intermediary capital is measured based on market values.

during the crisis as we have experienced after the Lehman failure in 2008.

Given that low-capital intermediaries are more highly leveraged and hold riskier stocks than high-capital intermediaries, it is expected that low-capital intermediaries will be more adversely affected by a negative shock in the stock market than high-capital intermediaries. Thus, the relative difference in capital ratios (measured in market values) should be higher during bad times. Figure 2 supports this notion. It presents the level and the dispersion of intermediary capital ratios, based on the largest 30 intermediaries in the U.S., from 1973/Q1 to 2016/Q4. In Panel A, the 25^{th} percentile of intermediary capital increases (decreases) faster during good (bad) times than the 75^{th} percentile of intermediary capital. Likewise, dispersion of capital ratios, defined as the difference between the 75^{th} and the 25^{th} percentile of intermediary capital, scaled by its 50^{th} percentile, shows a countercyclical variation in Panel B. Hence, the negative shock in the stock market induces the dispersion of capital ratios (as well as a portion of stocks held by high-capital intermediaries) to rise, which then drives up the aggregate risk aversion.[7] In the end, the shock in the dispersion of capital ratios generates a risk premium and is priced in the cross-section of stock returns.[8]

Furthermore, if a negative shock is sufficiently large and systematic, low-capital intermediaries may be faced with binding margin constraints (Brunnermeier and Pedersen, 2009)[9] and are forced to deleverage by selling off assets. In contrast, high-capital intermediaries do not face such constraints and may be able to buy those assets (Acharya and Viswanathan, 2011). As shown in Panel A of Figure 2, high-capital intermediaries experienced a rise in market capital while low-capital intermediaries lost their capital during the financial crisis. This is consistent with the argument that low-capital intermediaries sell their assets to high-capital intermediaries at prices lower than fundamental values during bad times.

[7]Note that if intermediaries are homogeneous in risk preference, the negative shock would alter the dispersion of capital ratios but not affect the aggregate risk aversion.

[8]In Section 6, I provide a model of heterogeneous intermediary capital where a more risk-averse specialist form an intermediary with higher capital and show that how the dispersion in an intermediary capital is priced in the cross-section of stock returns.

[9]The shock incurs losses in positions of low-capital intermediaries. If a cushion against the shock is not enough, low-capital intermediaries are likely to hit the margin constraints.

3 Data

I use the Center for Research in Security Prices (CRSP) database to obtain stock-level data for nonfinancial firms and intermediaries, the Compustat database to obtain nonfinancial firm- and intermediary-level data. I also use the Thomson Reuters Institutional (13F) Holdings database to retrieve holdings of intermediaries and their subsidiaries. To obtain the stock holdings of intermediaries, I manually match managers (*mgrno*) in the Institutional (13F) Holdings database and financial intermediaries (*gvkey*) in the Compustat database. In particular, I use a name matching algorithm of the Levenshtein distance to match names of the 13F managers with names of their holding companies up to ten and then review the initial matched-sets manually to finalize the matching.

The sample period covers January 1973 to December 2016. I choose January 1973 as the start because there was a large influx of intermediaries in the CRSP database in 1972. The empirical tests with the Institutional (13F) Holdings database cover 1980/Q1 to 2012/Q4. I exclude the period of 2013/1Q - 2016/4Q from the sample due to data quality problems in the Institutional (13F) Holdings database.[10]

3.1 Financial Intermediaries

The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code are 6000-6200 or 6712. The main empirical analyses focus on the largest 30 intermediaries based on market capitalization at the end of each quarter. This yields a list of 118 unique intermediaries over the sample period (See Table A.1 for the list). Since the largest 30 intermediaries hold the majority of assets in financial markets, their capital would be more relevant to determine the pricing kernel for financial assets. It seems defensible to focus on the largest 30 given that the number of U.S. primary dealers used in He, Kelly, and Manela (2017), ranges from 17 to 46, and there are 29 U.S. banks among the Global Systemically Important Banks (G-SIB) and the Systemically Important Financial Institution (SIFI) in 2017.[11]

Intermediary capital is measured using the quasi-market capital ratio, that is, the market value

[10] In 2013 onward, institutional 13F reports are often stale and omitted, certain securities may be excluded, and the number of shares are often reported inconsistently with splits.

[11] In Section 5.4, I also test using the largest 40 or 50 intermediaries.

of equity over the sum of the book value of debt and the market value of equity:

$$Capr = \frac{market\ value\ of\ equity}{market\ value\ of\ equity + book\ value\ of\ debt}. \tag{3.1}$$

Using intermediary capital defined in (3.1), I measure the dispersion of capital ratios in quater t as the difference between the 75^{th} and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile:

$$DISP_t^{Capr} = \frac{Capr_t^{75^{th}} - Capr_t^{25^{th}}}{Capr_t^{50^{th}}}. \tag{3.2}$$

Table 1 Panel A presents summary statistics for intermediaries. The statistics are averaged over quartiles based on intermediary capital. Several things are noteworthy. First, there are substantial variations in intermediary capital. High-capital intermediaries have six times higher capital ratio than low-capital intermediaries: 36.02% versus 5.68%. Second, high-capital intermediaries are far smaller than low-capital intermediaries, both in market value and in book value terms. Moreover, high-capital intermediaries tend to have lower book-to-market ratio and higher profitability and prior returns (i.e., momentum) than low-capital intermediaries. Market beta and asset growth are relatively stable across quartiles.

Note that book assets reported in Panel A do not comprise assets under management (AUM), which is an off-balance sheet item. In particular, AUM are the total market value of assets held by financial intermediaries on behalf of their clients while book assets are assets which they actually own in their balance sheet. The amount of AUM is not trivial relative to their book assets. In 2017, for instance, *JP Morgan Chase* had total AUM of \$2.03 trillion and book assets of \$2.53 trillion, and *BlackRock* had total AUM of \$6.29 trillion and book assets of \$0.22 trillion.[12] Importantly, stock holdings of financial intermediaries out of total AUM have grown significantly. Based on my sample of the largest 30 intermediaries in the U.S., the value-weighted average of the ratios of total stock holdings reported in the Institutional (13F) Holdings database over book assets was 6.5% in 1980 but increased to 26.0% in 2012.[13] Thus, it appears that trading behaviors of financial

[12] See annual reports of *JP Morgan Chase* (http://www.jpmorganchase.com/corporate/investor-relations/document/annualreport-2017.pdf) and *BlackRock* (http://ir.blackrock.com/Cache/1500109547.PDF?O=PDF&T=&Y=&D=&FID=1500109547&iid=4048287).

[13] The ratio is 14.4% on average over the entire sample period of 1980 - 2012.

intermediaries for stocks (primarily by their asset management arms) are sizable to their overall business operations.

Figure 2 shows intermediary capital over time. The shaded areas represent NBER recessions. Panel A shows that intermediary capital is closely related to the economic cycle. However, capital of high-capital intermediaries is countercyclical whereas that of low-capital intermediaries is procyclical. This becomes more stark when plotting the dispersion of capital ratios between high- and low-capital intermediaries and changes in the dispersion. Panel B illustrates that the dispersion of capital ratios is highly countercyclical, as discussed in Section 2. The dispersion of capital ratios is mostly less than one in good times whereas it peaks at 3.7 in the financial crisis. Consistently, changes in the dispersion become volatile in bad times.

3.2 Nonfinancial Firm Stocks

Test assets are common stocks of nonfinancial firms, identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). I also exclude tiny stocks (price less than \$5). For each stock, I estimate its exposure to the shock or change in the dispersion of capital ratios: the dispersion beta, defined as

$$\beta_t^{DISP} = \frac{Cov\left(\Delta DISP_t^{Capr}, r_t^i\right)}{Var\left(r_t^i\right)}. \tag{3.3}$$

I obtain β_t^{DISP} using 5-year rolling window regressions, $r_t^i - r_t^f = \alpha + \beta^{DISP,i}\Delta DISP_t^{Capr} + \beta^{MKT,i}MKT_t + \varepsilon_t^i$, where r_t^i is the quarterly return on nonfinancial firm stock, r_t^f is the one-month Treasury bill rate compounded over a quarter, MKT_t is the quarterly return on the market (i.e., the CRSP value-weighted index) less r_t^f.

Table 1 Panel B shows summary statistics for nonfinancial firm stocks based on the dispersion beta decile. First, there are substantial variations in the dispersion beta. While stocks in the lowest decile have dispersion beta of -0.45, stocks in the highest decile have the dispersion beta of +0.39. Second, stocks in the lowest decile tend to have higher market beta, book-to-market ratio, and prior returns, and smaller size than those in the highest decile. However, the differences in these characteristics are not so remarkable that one would argue that variations in the dispersion beta are simply spanned by other risk characteristics. Finally, stocks in the lowest decile earn annually

7.08%[14] higher (t-statistics = 5.04) than those in the highest decile.

4 Main Results

4.1 Intermediary Capital Ratios and Risk Preferences

Section 2 showed how intermediary capital is related to risk aversion of intermediaries, and Figure 1 provided preliminary evidence that intermediary capital seems to be negatively associated with risk-taking behavior of intermediaries. To formally test this, I estimate the risk preference of intermediaries from risk characteristics of stocks that intermediaries hold.

Table 2 presents how intermediary capital affects the risk characteristics of their holdings. I regress the risk characteristics of stocks held by intermediaries on their capital ratios. I use three risk measures: market beta, return volatility, and size (i.e., log of market capitalization) of stocks that the largest 30 intermediaries in the U.S. hold, reported in the Institutional (13F) Holdings database. Since stocks may be held by multiple intermediaries, intermediary capital and size are averaged within each stock using the number of shares held as a weight. I find the evidence that high-capital intermediaries tend to hold stocks with significantly lower betas and return volatility and higher market capitalization. This suggests that high-capital intermediaries seem to have higher risk aversion than low-capital intermediaries. In terms of economic significance, high-capital intermediaries hold stocks which exhibit 0.04 lower beta and 1.15% lower annual volatility[15] than low-capital intermediaries.[16]

If low-capital intermediaries (who are more highly leveraged) hold riskier stocks on their balance sheets, they would be more sensitive to an adverse shock than high-capital intermediaries, and then the price of their assets would drop further than that of high-capital intermediaries in bad times. Moreover, such an adverse shock would cause low-capital intermediaries facing margin constraints to sell their assets to deleverage (Brunnermeier and Pedersen, 2009). If the shock is large and systematic enough to induce all low-capital intermediaries to sell assets together, they have to sell at fire-sales prices. On the other hand, high-capital intermediaries, who do not face

[14] $7.08\% = (2.67\% - 2.08\%) \times 12$

[15] $0.04 = (36.02\% - 5.68\%) \times (-0.129); 1.15\% = (36.02\% - 5.68\%) \times (-0.019) \times \sqrt{4}$

[16] The economic significance presented in Table 2 appears to be smaller than in Figure 1. It is possible that these risk characteristics are rather persistent within a firm-level and then the firm fixed effect may lower the magnitude of the effect.

such margin constraints, may have sufficient capacity to absorb these assets and can buy these assets (Acharya and Viswanathan, 2011) at prices lower than fundamental values. As a result, net worth will be transferred from low- to high-capital intermediaries in bad times.

Figure 2 suggested that the dispersion of capital ratios is countercyclical. I now test this formally by regressing the dispersion of capital ratios on bad time dummy. I use two time measures: the financial crisis (from July 2007 to December 2009) and NBER recessions.

Table 3 shows that the dispersion of capital ratios increases to 2.51 (= 1.76 + 0.75) during the financial crisis in Column (1) and 1.85 (= 1.06 + 0.79) during NBER recessions in Column (4). Both findings are consistent with the dispersion of capital ratios being countercyclical. Importantly, it seems that this countercyclicality can be attributed to both high- and low-capital intermediaries. In Columns (2) and (3), low- (high-) capital intermediaries tend to have significantly lower (higher) capital during the financial crisis. Similarly, in Columns (5) and (6), low- (high-) capital intermediaries tend to have significantly lower (higher) capital during NBER recessions. As a result, high-capital intermediaries end up with even higher capital ratios whereas low-capital intermediaries have even lower capital ratios in bad times.

4.2 Asset Pricing Tests

In this section, I investigate how the dispersion of capital ratios is priced in the cross-section of stock returns. As discussed earlier, asymmetric responses to an adverse shock between high- and low-capital intermediaries lead to compositional changes in stock ownership, which in turn produce (countercyclical) time-varying risk aversion of a representative agent given that high-capital intermediaries are more risk-averse than low-capital intermediaries. Thus, a rise in the dispersion of capital ratios in bad times causes asset prices to decline and a risk premium to increase. This further implies that stocks that covary negatively with the shock in the dispersion of capital ratios would earn a higher risk premium and that stocks that covary positively with the shock in the dispersion of capital ratios would be hedging and should exhibit a lower risk premium. To test this hypothesis, I estimate the following Fama-MacBeth regressions:

$$r^i_{t+1} - r^f_{t+1} = \alpha + \lambda^{DISP}\beta^{DISP,i}_t + \sum_{k=1}^{K}\lambda^k\beta^{k,i}_t + \varepsilon^i_{t+1} \tag{4.1}$$

where the dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. Also, λ^{DISP} is the price of risk in the dispersion of capital ratios, and $\beta^{DISP,i}$ is the dispersion beta defined in Section 3.

Table 4 presents the results. After controlling for various risk characteristics, including the betas for the level of intermediary capital from Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017), I find that stocks with low dispersion betas earn significantly higher returns than stocks with high dispersion betas. In other words, dispersion of capital ratios is negatively priced in the cross-section of stock returns. In terms of economic significance, difference between the dispersion betas from the highest and the lowest deciles is 0.84 ($= 0.39 - (-0.45)$), and estimated price of risk in the dispersion of capital ratios ranges from -0.81 to -0.33. This implies that relative to stocks in the highest dispersion betas, stocks in the lowest dispersion betas earn an additional premium of 3.3% - 8.2% per annum.

Table 5 uses portfolio approaches to see if portfolios based on the dispersion beta earn abnormal returns. At the beginning of each month, stocks are sorted in deciles based on their dispersion betas (using NYSE breaks). Next, the portfolios are value-weighted in Panel A and equal-weighted in Panel B. I use five different factor models: FF5 is the Fama-French five factor model (Fama and French, 2015); FF5+PS adds the liquidity factor (Pastor and Stambaugh, 2003) to FF5; FF5+MOM adds the momentum factor (Jegadeesh and Titman, 1993) to FF5; FF5+AEM adds the intermediary leverage factor (Adrian, Etula, and Muir, 2014) to FF5; and FF5+HKM adds the intermediary capital factor (He, Kelly, and Manela, 2017) to FF5. Regardless of the model, I find that stocks with low dispersion betas earn significantly higher abnormal returns than stocks with high dispersion betas. Again, investors are likely to pay lower prices for stocks that have negative covariance with the shock in the dispersion of capital ratios, implying a higher risk premium. H - L portfolio earns monthly abnormal returns of -0.57% to -0.68%, which implies that estimated risk premium is 6.8% - 8.2% per annum. Overall, the results show that dispersion of capital ratios indeed is priced in the cross-section of stock returns.

4.3 Trading Activity of Intermediaries

As shown in Panel B of Figure 2, the dispersion of intermediary capital is countercyclical, which in turn leads to a countercyclical variation in aggregate risk aversion. As long as low-capital intermediaries experience more severe declines in their capital than high-capital intermediaries during bad times, asymmetric responses to the shock and compositional changes in the stock ownership can induce countercyclical variation in the aggregate risk aversion.[17] Interestingly, Table 3 shows that capital *increases* in high-capital intermediaries in spite of the fact that the high cost of capital would discount their market value and make it difficult for them to raise new capital during bad times. I argue that this pattern is consistent with low-capital intermediaries being forced to deleverage and selling off their assets to high-capital intermediaries at fire-sales prices during such times.

I now explore whether the trading activity of both sets of intermediaries is consistent with this. Ideally, I would like to identify the exact transaction date and the parties involved in the transaction to establish whether or not assets are fire-sold. Since the Thomson Reuters Institutional (13F) Holdings database provides neither the exact transaction date nor the parties involved in the transaction, I can only indirectly infer whether they are fire-sold from the trading volumes during the quarter and the trading gains, or abnormal returns, in the following quarter.[18] Note that the list of the largest 30 intermediaries can change every quarter and therefore an entry to (an exit from) the list may result in a spurious increase (decrease) in stock holdings, which potentially biases trading activities of the intermediaries. To avoid this issue, I include all intermediaries that have been listed as the largest 30 intermediaries at least once.

I perform the following regressions:

$$Stock\ Purchases^I_{m,t} = \gamma_0 + \gamma_1 DISP^{Capr}_t + Controls_{m,t} + FE + \varepsilon^I_{m,t} \tag{4.2}$$

$$Stock\ Sales^I_{m,t} = \gamma_0 + \gamma_1 DISP^{Capr}_t + Controls_{m,t} + FE + \varepsilon^I_{m,t} \tag{4.3}$$

where m represents 13F managers, and $Stock\ Purchases^I_t$ and $Stock\ Sales^I_t$, $I \in \{H, L\}$, are defined as the total amount of stocks bought and sold, respectively, in quarter t, measured in billion dollars. High- and low-capital intermediaries are the ones above and below the 50^{th} percentile of intermediary capital. The dispersion of capital ratios ($DISP^{Capr}_t$), defined in (3.2), is a proxy

[17] That means increase in capital of high-capital intermediaries is not a necessary condition for the countercyclical variation in the aggregate risk aversion.

[18] That is, the agents who bought (sold) an asset at a price lower than the fundamental value would earn positive (negative) abnormal returns in the subsequent period.

for bad times, as aggregate risk aversion increases with the dispersion of capital ratios. Control variables include intermediary size (measured as the log of market capitalization) and portfolio size (measured as the log of portfolio size of 13F manager). For trading gains, I run the following regression:

$$\begin{aligned} \textit{Trading Gains}^{I}_{m,t+1} &= \theta_0 + \theta_1 \mathbb{1}(\textit{Intermediary Capital}_t = \textit{Low}) \times DISP^{Capr}_t \\ &+ \theta_2 \mathbb{1}(\textit{Intermediary Capital}_t = \textit{Low}) + \theta_3 DISP^{Capr}_t + \textit{Controls}_{m,t+1} + FE + \varepsilon^{I}_{m,t+1}. \end{aligned} \tag{4.4}$$

where $\textit{Trading Gains}^{I}_{m,t+1} \equiv \dfrac{\sum |n_t| p_t \times \alpha_{t+1}}{\sum |n_t| p_t}$, n_t is the signed number of shares traded, p_t is the price at the end of quarter t, and α_{t+1} is the abnormal return in the quarter $t+1$, estimated using the Fama-French five factor model (Fama and French, 2015).[19] $\mathbb{1}(\textit{Intermediary Capital}_t = \textit{Low})$ is an indicator function which takes the value of one if the intermediary capital ratio of a 13F manager is lower than the median in quarter t and zero otherwise.

Table 6 shows the regressions results for trading volume from Equations (4.2) and (4.3) for high-capital intermediaries (Panel A) and low-capital intermediaries (Panel B). First, as the dispersion of capital ratios increases, high-capital intermediaries do not significantly reduce stock purchases and raise stock sales (Columns (1) and (3) in Panel A). However, as the dispersion of capital ratios increases, low-capital intermediaries do significantly reduce their stock purchases and raise their stock sales (Columns (1) and (2) in Panel B). These results provide evidence that low-capital intermediaries deleverage by selling off assets while high-capital intermediaries do not exhibit similar behavior.

More importantly, I am interested in whether high-capital intermediaries purchase stocks that low-capital intermediaries sell during bad times and, similarly, whether low-capital intermediaries sell stocks that high-capital intermediaries buy during such times. Since the identity of the parties involved in the transaction is not observable from the data, I use the change in ownership by high- and low-capital intermediaries to classify the stocks that high-capital intermediaries purchase and low-capital intermediaries sell. Specifically, I identify the stocks that high-capital intermediaries

[19] Note that $n_t > 0$ represents stock purchases and $n_t < 0$ represents stock sales. Thus, $\textit{Trading Gains}^{I}_{m,t+1}$ from stock purchases are defined as $\frac{\sum \mathbb{1}(n_t>0)|n_t|p_t \times \alpha_{t+1}}{\sum |n_t| p_t}$, and $\textit{Trading Gains}^{I}_{m,t+1}$ from stock sales are defined as $\frac{\sum \mathbb{1}(n_t<0)|n_t|p_t \times \alpha_{t+1}}{\sum |n_t| p_t}$.

purchase as ones in which they raise their holdings during quarter t ($\Delta IO^H > 0$); and the stocks that low-capital intermediaries sell as ones in which they reduce their holdings during quarter t ($\Delta IO^L < 0$).

Column (2) of Panel A shows that as the dispersion of capital ratios increases, high-capital intermediaries purchase significantly more stocks that low-capital intermediaries sell. Also, Column (3) of Panel B indicates that as the dispersion of capital ratios increases, low-capital intermediaries sell significantly more stocks that high-capital intermediaries purchase. It is apparent that there are asset transfers from low-capital intermediaries to high-capital intermediaries during bad times.

Table 7 summarizes the trading gains of high- and low-capital intermediaries to show at what price they trade stocks during bad times, estimating Equation (4.4). There are two sources of trading gains that intermediaries can earn: stocks bought can appreciate in value, and stocks sold can depreciate in value. The latter is not a realized return, but more related to forgone returns on sales. If low-capital intermediaries sell stocks to high-capital intermediaries at fire-sale prices (i.e., at prices lower than fundamental values), one would expect that high-capital intermediaries earn positive returns on stock purchases, and low-capital intermediaries lose in terms of forgone returns on sales in the following period when stock prices return to their fundamental values. In Pane A, I find the evidence that is consistent with the argument above. As the dispersion of capital ratios increases, low-capital intermediaries earn lower abnormal trading gains than high-capital intermediaries in the following quarter. Also, the difference is mainly attributed to the price depreciation of stocks sold in Column (3), implying that low-capital intermediaries suffer losses from stock sales.

Panels B and C present the trading gains separately for high- and low-capital intermediaries. In both panels, buying (selling) stocks would result in positive (negative) returns during bad times, implying that stock prices, in general, deflate during bad times. However, the trading gains, reported in Panel A, are mainly attributed to positive returns from purchases on stocks by high-capital intermediaries (Column (2) of Panel B) and negative returns from forgone losses on stock sales by low-capital intermediaries (Column (3) of Panel C). As the dispersion of capital ratios rose to 2.51 in the financial crisis as in Table 3, high- (low-) capital intermediaries earn (lose) abnormal returns of 1.51% (1.81%)[20] from purchases (sales) of stocks over the following quarter $t + 1$ in the

[20] $1.51\% = 2.51 \times 0.60\%$ and $1.81\% = 2.51 \times 0.72\%$

financial crisis.[21]

Altogether, the findings in Table 6 and 7 are consistent with the hypothesis that low-capital intermediaries sell their stocks to high-capital intermediaries at fire-sale prices during bad times.

5 Additional Tests and Robustness Checks

This section presents the results of additional tests to establish the robustness of the empirical findings in Section 4.

5.1 Trading Activity of Intermediaries and Risk Characteristics of Stocks

Section 4.3 investigated trading activity by intermediaries with different capital ratios during bad times. This leads to a question of which stocks these intermediaries trade. In particular, when low-capital intermediaries are forced to sell assets after being hit by an adverse shock, they may be reluctant to sell stocks that have experienced severe price collapses (i.e., stocks with low dispersion betas) to avoid huge losses from selling those stocks. However, risk-averse high-capital intermediaries may not be interested in buying assets from low-capital intermediaries unless prices have dropped sufficiently. I now address this by directly investigating changes in holdings of intermediaries at the stock-level.

Table 8 presents the trading volume of stocks by high- and low-capital intermediaries in Panel A and B, respectively. Trading volume is defined as the dollar amount of net purchases in a stock for a quarter t scaled by the manager's portfolio size. As in Table 6 and 7, high- and low-capital intermediaries have capital ratios above and below the 50^{th} percentile, respectively, of the largest 30 intermediaries in the U.S. High- (Low-) β^{DISP} stocks belong to the highest (lowest) three deciles in the dispersion beta. Stocks in the middle four deciles are denoted as Med-β^{DISP}.

Panel A shows that high-capital intermediaries purchase significantly larger amounts of stocks with Low-β^{DISP} than those with Med- or High-β^{DISP} when the dispersion of capital ratios is high (i.e., during bad times). In contrast, Panel B provides evidence that low-capital intermediaries sell significantly larger amounts of stocks with Med-β^{DISP} than those with Low- or High-β^{DISP} when the dispersion of capital ratios is high. Interestingly, the findings in Table 8 document that there

[21] As an extreme case, for 2008/Q3-Q4, high-capital intermediaries earned abnormal trading gains of 4.8% while low-capital intermediaries suffered abnormal trading losses of 5.3%.

is a *trade mismatch* between high- and low-capital intermediaries during bad times. High-capital intermediaries are so risk averse that they are willing to buy only stocks that have sufficiently fallen in price. At the same time, low-capital intermediaries do not want to sell those assets if they believe that prices have temporarily dropped below fundamental values and will recover again. Rather, they choose to sell stocks that have experienced modest price drop.

5.2 Controlling Industry Effect

Equation (4.1) can be misspecified if the dispersion beta is clustered by industry. As discussed in Lyon, Barber, and Tsai (1999) and Johnson, Moorman, and Sorescu (2009), this industry clustering may lead to a spurious relation between risk characteristics being tested and stock returns. To rule out the possibility of the industry clustering in the dispersion beta, I include industry fixed effect in the Fama-MacBeth regressions as follows:

$$r_{t+1}^{i} - r_{t+1}^{f} = \alpha + \lambda^{DISP}\beta_t^{DISP,i} + \sum_{k=1}^{K}\lambda^{k}\beta_t^{k,i} + Z^{j} + \varepsilon_{t+1}^{i} \tag{5.1}$$

where Z^j is the industry fixed effect. For each month, stocks are assigned to each industry based on SIC codes and the Fama-French 10-industry classification.

Table 9 shows the estimation results of Equation (5.1). The dispersion beta (β^{DISP}) appears to be negatively priced in the cross-section of stock returns. The estimated price of risk for the dispersion beta is similar to the one without the industry effect in Table 4, implying that the relation between the dispersion beta and stock returns is hardly influenced by any unobserved heterogeneity across industry (e.g., the industry clustering).

5.3 Balancing Size of High- and Low-Capital Intermediaries

When the dispersion of capital ratios is defined in Equation (3.2), the X^{th} percentile of the intermediary capital of the largest 30 intermediaries in the U.S. is simply based on the number of the intermediaries and does not account for the size of the intermediaries. Summary statistics in Panel A of Table 1 report that high-capital intermediaries tend to be smaller than low-capital intermediaries. Therefore, total size of intermediaries above the 75^{th} percentile of intermediary capital is lower than that below its 25^{th} percentile.[22]

To measure the X^{th} percentile of the intermediary capital by incorporating the size of intermediaries, I redefine the dispersion of capital ratios so that the total market capitalization of high- and low-capitalization are similar: the difference between the 75^{th} percentile and the 10^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile.[23]

$$DISP_t^{Capr} = \frac{Capr_t^{75^{th}} - Capr_t^{10^{th}}}{Capr_t^{50^{th}}} \tag{5.2}$$

Table 10 reports the results based on Equation (5.2). Similar to Table 4, I continue to find that the dispersion beta (β^{DISP}) is significantly and negatively priced in the cross-section of stock returns.

5.4 Using Largest 40 or 50 Intermediaries

The main results in Section 4 define financial intermediaries to be the largest 30 intermediaries. Ideally, I would like to include all intermediaries that are large enough to make their capital important in characterizing the pricing kernel. However, there is no clear-cut way to determine how many intermediaries are marginal investors. To test if my choice of the number of intermediaries affects the results, I now alternatively measure the dispersion of capital ratios using the largest 40 or 50 intermediaries.

Table 11 summarizes the results. In Columns (1) - (3), I find that the dispersion beta (β^{DISP}) based on the largest 40 intermediaries is still significantly priced in the cross-section of stock returns, but the price of risk is rather smaller than in Table 4. In Columns (4) - (6), the results based on the largest 50 intermediaries are marginally significant or insignificant. It appears that at least some intermediaries outside the largest 40 intermediaries can be inappropriate to be viewed as marginal investors.

[22] Total market capitalizations above the 75^{th} percentile and below the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S. are $93 billion and $223 billion on average.

[23] Total market capitalizations below the 10^{th} and 11^{th} percentile are $71 billion and $103 billion, respectively, on average. For simplicity, I report the results based on the 10^{th} percentile, but the results based on the 11^{th} percentile are also significant at the 1% or 5% level.

5.5 Using Book Capital Ratio

In Section 4, I measure intermediary capital based on market values. It is interesting to examine if consistent results are obtained when the book capital ratio is used to estimate the dispersion beta. As discussed in He, Kelly, and Manela (2017), if intermediaries perfectly implement mark-to-market for their holdings of financial assets, intermediary capital measured based on market values and book values should be aligned. When the intermediaries are selling off assets to reduce debt, the book capital ratio continues to rise. However, if a high discount rate during bad times pushes down the market value of capital faster than the debt decreases, the market capital ratio declines (Santos and Veronesi, 2018). Therefore, the book capital ratio could move in the opposite direction as the market capital ratio. Furthermore, it may seem hard to argue that the change in intermediaries' book capital ratio matters in the pricing kernel, because the book capital ratio is largely determined endogenously by intermediaries. Nevertheless, I now rerun my analyses using book capital ratios.

Figure 3 shows the level and the dispersion of capital ratios measured using book values. Different from Figure 2, which uses market values, low-capital intermediaries raise their capital ratios in the financial crisis (i.e., they deleverage) (See Panel A). Nevertheless, the dispersion of capital ratios in Panel B indicates countercyclical variation, although it seems less volatile than the dispersion of capital ratios in market values shown in Panel B of Figure 2.[24]

Table 12 repeats Table 4 but uses the book capital ratio to define intermediary capital. Not surprisingly, the dispersion beta (β^{DISP}) is not significantly priced in the cross-section of stock returns even though the signs on the price of the risk remain negative as in Table 4. These results suggest that it is more appropriate to measure intermediary capital in market values than in book values to obtain the pricing kernel of marginal investors.

5.6 Subsample Tests

Table 13 repeats Table 4 for subsample periods to test the effect of the dispersion beta (β^{DISP}) on the cross-section of stock returns changes over time. In Panel A, the subsample periods are before 2000 and after 2000. I find that the dispersion beta is priced in the cross-section of stock returns

[24] The 75^{th} (25^{th}) percentile of the *quasi-market* capital ratio of the largest 30 intermediaries in the U.S. and the 75^{th} (25^{th}) percentile of the *book* capital ratio of the largest 30 intermediaries in the U.S. are positively correlated at 0.86 (0.56). Also, the correlation between the dispersion of capital ratios in market value and book value terms is 0.78.

over the subsample periods. The effect remains statistically and economically significant.

As shown in Figure 2, dispersion of intermediary capital is unusually high during the financial crisis (or similarly during NBER recessions). It may be possible that the dispersion beta is priced in the cross-section of stock returns only in economic bad times, not normal times. In Panel B of Table 13, I test this possibility by excluding the financial crisis in Columns (1) - (3) or NBER recessions in Columns (4) - (6) from the sample period. I continue to find the significant price of risk for the dispersion beta in these subsample periods and confirm that my main results are not driven by the bad times.

6 Model of Heterogeneous Intermediary Capital

Based on the empirical findings in the previous section, I develop a model of heterogeneous intermediary capital in which the dispersion of intermediary capital is priced in the cross-section of stock returns. The model provides a mechanism that a risk-averse (risk-tolerant) manager form a high- (low-) capital intermediary and that asymmetric responses to an adverse shock between the two intermediaries lead to a countercyclical variation in aggregate risk aversion. The model also shows that the dispersion of intermediary capital generates a sizable risk premium in addition to that attributable to the level of intermediary capital.

6.1 Setup

The timeline of the economy is described in Figure 4. The economy is populated with two specialists $\{H, L\}$ and one household $\{hh\}$. There are three periods, $t = \{0, 1, 2\}$. At $t = 0$, the two specialists receive an endowment of $e^H = e^L$. As shown in Section 6.2, specialist H has a more persistent habit than specialist L in their utility functions. The household arrives at $t = 1$ with an endowment of e^{hh}. There are two types of assets, a risky asset, a, and a risk-free asset, f, available to invest at $t = \{0, 1\}$.

Following He and Krishnamurthy (2013), the household cannot directly invest in the risky asset, but can invest in the risk-free asset.[25] Specialists are able to invest both in the risky asset

[25] Households' participation in financial markets can be limited due to lack of skills (van Rooij, Lusardi, and Alessie, 2011) or fixed participation costs (Vissing-Jorgensen, 2003) among others. Although the households' participation is not completely limited in reality, I make this restriction to make sure that that households are not marginal investors.

and the risk-free asset without a short-sale constraint. Each specialist forms an intermediary using her own wealth and funds provided by the household. Specifically, at $t = 1$, the household allocates ψ_1^H of her (post-consumption) wealth, w_1^{hh}, to specialist H and ψ_1^L of her wealth to specialist L to purchase equity capital of intermediaries. Thus, intermediary capital would be $\kappa_1^H \equiv w_1^H + \psi_1^H w_1^{hh}$ for intermediary H and $\kappa_1^L \equiv w_1^L + \psi_1^L w_1^{hh}$ for intermediary L.

The return on the risky asset, a, follows a stochastic process:

$$r_t^a = \mu_t + \sigma_t \varepsilon_t, \quad \varepsilon_t \sim i.i.d.\mathcal{N}(0,1). \tag{6.1}$$

Denote α_t^I to be the portion of the risky asset in specialists' portfolios. $1 - \alpha_t^I$ is the portion of the risk-free asset in their portfolios. The return on intermediary capital is then

$$r_{t+1}^I = \alpha_t^I \left(r_{t+1}^a - r_{t+1}^f \right) + r_{t+1}^f \tag{6.2}$$

where $I \in \{H, L\}$ and r_t^f is the return on the risk-free asset. The total supply of the risky asset is normalized to one.

$$\alpha_t^H \left(w_t^H + \psi_t^H w_t^{hh} \right) + \alpha_t^L \left(w_t^L + \psi_t^L w_t^{hh} \right) = 1. \tag{6.3}$$

The risk-free asset, issued by specialists/intermediaries, is in zero net supply.

$$\left(1 - \alpha_t^H\right) \left(w_t^H + \psi_t^H w_t^{hh} \right) + \left(1 - \alpha_t^L\right) \left(w_t^L + \psi_t^L w_t^{hh} \right) + \left(1 - \psi_t^H - \psi_t^L\right) w^{hh} = 0. \tag{6.4}$$

6.2 Specialist Problem

Specialists maximize their expected utility over lifetime, $t \in \{0, 1, 2\}$ under budget constraints. To incorporate time-varying risk aversion of the specialists, I consider the utility function accounting for a habit.

$$\max_{\{C_t^I,\alpha_t^I\}} E\left[\sum_{t=0}^{2} e^{-\rho t} u\left(C_t^I, X_t^I\right)\right] \quad \text{subject to} \tag{6.5}$$

$$w_{t+1}^I = w_t^I\left(1+r_{t+1}^I\right) - C_{t+1}^I = w_t^I + w_t^I\alpha_t^I\left(r_t^a - r_t^f\right) + w_t^I r_t^f - C_{t+1}^I \tag{6.6}$$

where $u\left(C_t^I, X_t^I\right) = \frac{\left(C_t^I - X_t^I\right)^{1-\gamma}}{1-\gamma}$. C_t^I is the specialists' consumption, X_t^I is their habits, and γ is a curvature parameter. The habits, X_t^I, are determined by the specialists' history of consumption. To account for the heterogeneous risk aversion of the two specialists, I suppose that specialist H has a more persistent habit than specialist L.

$$X_t^I = \begin{cases} \eta \sum_{j=1}^{t} \left(\phi^I\right)^j C_{t-j}^I & \text{if } t > 0 \\ 0 & \text{if } t = 0 \end{cases} \tag{6.7}$$

where $0 < \phi^L < \phi^H \leq 1$ and $\eta < 1$.[26]

Next, I obtain the first-order condition for (6.5) and (6.6) to solve specialists' consumption:

$$\begin{aligned} E\Big[\left(C_0^I\right)^{-\gamma} - \left\{\eta\phi^I - \left(1+r_1^I\right)\right\} e^{-\rho}\left(C_1^I - \eta\phi^I C_0^I\right)^{-\gamma} \\ - \left\{\phi^I + \left(1+r_1^I\right)\right\}\eta\phi^I e^{-2\rho}\left(C_2^I - \eta\phi^I C_1^I - \eta\left(\phi^I\right)^2 C_0^I\right)\Big] = 0. \end{aligned} \tag{6.8}$$

Assuming the consumption growth of the two specialists to be a random walk (Campbell and Cochrane, 1999), $\Delta c_1 = g + \sigma_c\varepsilon_1$, where $\Delta c_1 = log\frac{C_1}{C_0}$, specialists' consumption at $t = 0$ is given by:

$$C_0^I = E\left[C_2^I\left(\left\{\frac{Z_1^I\left(G-\eta\phi^I\right)^{-\gamma}+1}{Z_2^I}\right\}^{-\frac{1}{\gamma}} + \eta\phi^I G + \eta\left(\phi^I\right)^2\right)^{-1}\right] \tag{6.9}$$

where $G \equiv exp\left(g+\sigma_c\varepsilon_1\right)$, $Z_1^I \equiv \left[\left(1+r_1^I\right) - \eta\phi^I\right]e^{-\rho} > 0$, and $Z_2^I \equiv \left[\phi^I + \left(1+r_1^I\right)\right]\eta\phi^I e^{-2\rho} > 0$. Since $\partial C_0^I/\partial\phi^I < 0$, $C_0^H < C_0^L$ and $C_1^H < C_1^L$. This is intuitive, as argued in Campbell and

[26] Note that if $\phi = 0$, an agent does not develop a habit. The utility function in (6.5) reduces to a simple CRRA utility function.

Cochrane (1999): existence of the habit term, X_t^I, would lower the lifetime marginal utility of consumption today because consumption today reduces future utilities. Therefore, specialist H who exhibits a more persistent habit consumes less than specialist L.

Further, the Arrow-Pratt measure of relative risk aversion for specialists is:

$$\Gamma_t^I = -\frac{C_t^I u''\left(C_t^I - X_t^I\right)}{u'\left(C_t^I - X_t^I\right)} = \frac{\gamma}{S_t^I}. \tag{6.10}$$

where $S \equiv \frac{C-X}{C}$ is the surplus consumption ratio. Since $X_0^H = X_0^L = 0$, the surplus consumption ratio at $t = 0$ is equal to one, and then risk aversion of two specialists is $\Gamma_0^H = \Gamma_0^L = \gamma$. Importantly enough, a more persistent habit for specialist H leads to the lower surplus consumption ratio, thereby increasing risk aversion of specialist H at $t = 1$. Based on their risk aversion, specialists will choose optimal portfolios using the risky asset and the risk-free asset at $t = 1$. This is presented in Proposition 1.

Proposition 1 (Risk Aversion and Portfolio Choices)**.**
(i) Specialist H has higher risk aversion than specialist L at $t = 1$.

$$\Gamma_1^H > \Gamma_1^L. \tag{6.11}$$

(ii) Specialist L demands a higher portion of her wealth into the risky asset than specialist H at $t = 1$.

$$\alpha_1^H < \alpha_1^L. \tag{6.12}$$

Proof: See Appendix A.1
As in He and Krishnamurthy (2013), α_t^I is typically greater than one, implying that specialists take leveraged positions by issuing the risk-free asset to the household. Proposition 1 shows that the risk-tolerant specialist (type = L) takes higher leverage than the risk-averse specialist (type = H) at $t = 1$.

6.3 Household Problem

The household maximizes expected lifetime utility over $t \in \{1, 2\}$ under the following constraints. First, a budge constraint asserts that the household's (post-consumption) wealth will be allocated into equity capital of intermediaries and the risk-free asset. Second, there is a minimum capital requirement to have a viable intermediary sector. Thus, the household is required to purchase at least a certain amount of equity capital from the intermediaries. Finally, the household limits the amount of equity capital purchased from each intermediary.[27] In particular, the household purchases equity capital of each intermediary up to a multiple (m) of w_t^I. w_t^I refers to "skin in the game" for specialists (He and Krishnamurthy, 2013).

$$\max_{\{C_t^{hh}, \psi_t^H, \psi_t^L\}} E\left[\sum_{t=1}^{2} e^{-\rho t}\left(-\frac{e^{-AC_t^{hh}}}{A}\right)\right] \quad \text{subject to} \tag{6.13}$$

$$w_{t+1}^{hh} = \psi_t^H w_t^{hh} r_{t+1}^H + \psi_t^L w_t^{hh} r_{t+1}^L + \left(1 - \psi_t^H - \psi_t^L\right) w_t^{hh} r_{t+1}^f - C_{t+1}^{hh} \tag{6.14}$$

$$\kappa_t^H + \kappa_t^L = w_t^H + w_t^L + w_t^{hh}\left(\psi_t^H + \psi_t^L\right) \geq \tilde{\kappa} \tag{6.15}$$

$$\psi_t^I w_t^{hh} \leq m w_t^I, \quad I \in \{H, L\} \tag{6.16}$$

where C_t^{hh} is the household's consumption, and $A > 0$ is an absolute risk aversion of the household. (6.14) - (6.16) represent the budget constraint, the minimum capital requirement, and the capital constraint, respectively.

Suppose that the household's consumption is normally distributed. The household's objective function is then equivalent to:

$$\max_{\{\psi_t^H, \psi_t^L\}} \psi_t^H E_t\left[r_{t+1}^H - r_{t+1}^f\right] + \psi_t^L E_t\left[r_{t+1}^L - r_{t+1}^f\right] - \frac{A}{2} Var_t\left[\psi_{t+1}^H r_{t+1}^H + \psi_{t+1}^L r_{t+1}^L\right] \tag{6.17}$$

subject to

$$w_t^H + w_t^L + w_t^{hh}\left(\psi_t^H + \psi_t^L\right) \geq \tilde{\kappa}$$

$$\psi_t^I w_t^{hh} \leq m w_t^I, \quad I \in \{H, L\}$$

[27] Equivalently, this implies that an intermediary faces a capital constraint.

Using Equation (6.2), the first-order conditions with respect to ψ_t^H and ψ_t^L as well as inequality constraints follow that

$$\alpha_t^H E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^H\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right] - \left(\theta_t^H + \theta_t^C\right)w_t^{hh} = 0 \tag{6.18}$$

$$\alpha_t^L E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^L\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right] - \left(\theta_t^L + \theta_t^C\right)w_t^{hh} = 0 \tag{6.19}$$

$$\theta_t^C\left[\tilde{\kappa} - w_t^H - w_t^L - w_t^{hh}\left(\psi_t^H + \psi_t^L\right)\right] = 0 \tag{6.20}$$

$$\theta_t^H\left(\psi_t^H w_t^{hh} - m w_t^H\right) = 0 \tag{6.21}$$

$$\theta_t^L\left(\psi_t^L w_t^{hh} - m w_t^L\right) = 0 \tag{6.22}$$

where θ_t^C, θ_t^H, and θ_t^L are the Lagrange multipliers associated with constraints. Here, I focus on the most realistic case where the minimum capital requirement in (6.15) and the capital constraints in (6.16) are slack (i.e., $\theta_t^C = \theta_t^H = \theta_t^L = 0$).[28]

Proposition 1 confirms that specialist H has higher risk aversion than specialist L, which leads to the tighter capital constraint for specialist L than specialist H from (6.16). Therefore, the household is more willing to purchase equity capital of intermediary H than that of intermediary L. I summarize the household's allocation in Proposition 2.

Proposition 2 (Household's Allocation)**.** *There is a minimum capital* $\tilde{\kappa}^* \equiv \dfrac{2}{A}\dfrac{\mu_t - r_t^f}{\sigma_t^2}\dfrac{w_t^{hh}}{\alpha_t^H + \alpha_t^L} + \left(w_t^H + w_t^L\right)$ *that satisfies* $\psi_t^H > \psi_t^L$ *where* $Y_t \equiv \frac{1}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}$*,*

$$\psi_t^H \geq \frac{\alpha_t^L\frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\alpha_t^L - \alpha_t^H}, \quad \text{and} \quad \psi_t^L \leq \frac{Y_t - \alpha_t^H\frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}}{\alpha_t^L - \alpha_t^H}. \tag{6.23}$$

In other words, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^*$*, the household purchases more equity capital from intermediary* H *than from intermediary* L *(i.e.,* $\psi_t^H > \psi_t^L$*).*

Proof: See Appendix A.1

As discussed in Section 6.2, the specialist with a more persistent habit consumes less at $t \in \{0, 1\}$. This further implies that specialist H has larger wealth available to invest in intermediary than specialist L at $t = 1$. Also, Proposition 2 argues that the household allocates a larger portion of her wealth to intermediary H than to intermediary L. Hence, the intermediary capital, defined

[28] Other cases will be considered in Appendix A.2.

as the sum of the wealth of a specialist and the amount that the household allocates to purchase equity capital of an intermediary, is higher in intermediary H than in intermediary L:

Proposition 3 (Intermediary Capital)**.** *If the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^*$, the specialist who has higher (lower) risk aversion forms an intermediary with higher (lower) capital.*

$$\kappa_1^H = w_1^H + \psi_1^H w_1^{hh} > \kappa_1^L = w_1^L + \psi_t^L w_1^{hh}. \tag{6.24}$$

Proof: See Appendix A.1

6.4 Asset Prices

Having established in Proposition 3 that a more risk-averse specialist attracts more equity capital from the household to form an intermediary than a less risk-averse specialist, I derive a pricing equation for the risky asset, a. In this economy, the low-capital intermediary L is more highly leveraged than the high-capital intermediary H, (i.e., $\alpha_t^L > \alpha_t^H$), so that the risky asset is held more in the low-capital intermediary. When a negative shock arrives in this asset, the low-capital intermediary loses more than the high-capital intermediary. Thus, the relative difference in capital between the high- and low-capital intermediary rises. Moreover, since the low- (high-) capital intermediary holds a relatively smaller (larger) portion of the risky asset in bad times, the aggregate risk aversion and the risk premium rise in bad times.

Suppose an agent's risk-bearing capacity is a function of her consumption and risk aversion. Following Bhamra and Uppal (2009), Gârleanu and Pedersen (2011), and Gârleanu and Panageas (2015) among others, the sum of each agent's risk-bearing capacity is the risk-bearing capacity of the economy as a whole. That is:

$$\frac{C^H}{\Gamma^H} + \frac{C^L}{\Gamma^L} \equiv \frac{C^H + C^L}{\Gamma}, \quad \text{or} \quad \Gamma \equiv \frac{1}{\dfrac{C^H}{C^H + C^L}\dfrac{1}{\Gamma^H} + \dfrac{C^L}{C^H + C^L}\dfrac{1}{\Gamma^L}} \tag{6.25}$$

where Γ is the aggregate risk aversion of the economy.

From Equation (6.1), a shock, ε_t, arrives in the risky asset at $t = 2$. Because of the different leverage positions of the two intermediaries, the shock is negatively related to the dispersion in intermediary capital, defined as $DISP_t^{Capr} \equiv \frac{\kappa_t^H - \kappa_t^L}{\kappa_t}$. Note that a consumption function is a monotonic transformation of wealth. This results in the negative relationship between the shock in the risky asset and the dispersion in specialists' consumption. In other words, upon arrival of a positive (negative) shock, the portion of capital held by intermediary L increases (decreases), and consequently, the portion of consumption of specialist L rises (falls) as well. These arguments are summarized in Proposition 4.

Proposition 4 (Dispersion of Intermediary Capital and of Specialists' Consumption)**.**
(1) The positive (negative) shock in the risky asset at $t = 2$ leads to a decline (rise) in the dispersion in intermediary capital.

$$\varepsilon_2 \left(\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} \right) < 0 \tag{6.26}$$

(2) The positive (negative) shock in the risky asset at $t = 2$ leads to a decline (rise) in the dispersion in specialists' consumption.

$$\varepsilon_2 \left(\frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} - \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]} \right) < 0 \tag{6.27}$$

Proof: See Appendix A.1

Since a negative shock lowers the surplus consumption ratio (i.e., $S = \frac{C-X}{C}$) of the agents who exhibit habits in their utility function, risk aversion of each agent is countercyclical. More importantly, the compositional change in specialists' consumption induced by the shock also has an impact on the aggregate risk aversion of the economy. That is, the aggregate risk aversion gets closer toward that of a risk-averse (risk-tolerant) agent upon arrival of the negative (positive) shock. Overall, if a negative shock arrives in the risky asset, $\varepsilon_2 < 0$, then aggregate risk aversion rises. Similarly, if a positive shock arrives in the risky asset, $\varepsilon_2 > 0$, then aggregate risk aversion falls.

Proposition 5 (Countercyclical Aggregate Risk Aversion)**.** *At $t = 2$, the shock in the risky asset and aggregate risk aversion are inversely related.*

$$\varepsilon_2 \Gamma_2 < 0. \tag{6.28}$$

Proof: See Appendix A.1

How does the dispersion of intermediary capital affect aggregate risk aversion? It is evident from Proposition 4 that the change in the dispersion of intermediary capital gives rise to the change in the dispersion of specialists' consumption. Thus, when the dispersion of intermediary capital rises (falls), specialist H will enjoy a larger (smaller) stake in consumption than specialist L. This compositional change subsequently affects the aggregate risk aversion.

Proposition 6 (Dispersion of Intermediary Capital and Aggregate Risk Aversion)**.** *At $t = 2$, the dispersion of intermediary capital is positively associated with the aggregate risk aversion of the market:*

$$\left(\frac{\kappa_2^H - \kappa_2^L}{\kappa_2}\right)\Gamma_2 > 0. \tag{6.29}$$

Proof: See Appendix A.1

To emphasize the important role of heterogeneous preference between the two specialists in the aggregate risk aversion, suppose that if specialists are homogeneous in risk preference and the leverage position accordingly, intermediaries will be symmetrically affected from the shock. This further implies that the shock would not change the dispersion of intermediary capital. If so, the positive relation between the dispersion of intermediary capital and the aggregate risk aversion of the market in Proposition 6 no longer holds, and then the dispersion of intermediary capital does not affect the aggregate risk aversion of the market.

Next, I derive the Euler equation for the risky asset, a, that incorporates Proposition 6. In a complete market, specialists' discount factor, M_t, follows that

$$M_t = \xi^H e^{-\rho t}\left(C_t^H - X_t^H\right) = \xi^L e^{-\rho t}\left(C_t^L - X_t^L\right) \tag{6.30}$$

where ξ^H and ξ^L are Pareto weights for the specialists. Equation (6.30) implies that $C_t^H - X_t^H =$

$\left(M_t/\xi^H e^{-\rho t}\right)^{-\frac{1}{\gamma}}$ and $C_t^L - X_t^L = \left(M_t/\xi^L e^{-\rho t}\right)^{-\frac{1}{\gamma}}$.[29] Therefore, the Euler equation for the representative investor is

$$E_t\left[\frac{M_{t+1}}{M_t}R_{t+1}^a\right] = E_t\left[e^{-\rho}\frac{(C_{t+1}-X_{t+1})^{-\gamma}}{(C_t-X_t)^{-\gamma}}R_{t+1}^a\right]$$
$$= E_t\left[e^{-\rho}\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left(\frac{S_{t+1}}{S_t}\right)^{-\gamma}R_{t+1}^a\right] = 1. \tag{6.31}$$

A log-linear approximation leads to the following equation.[30]

$$E_t\left[r_{t+1}^a - r_{t+1}^f\right] + \frac{1}{2}Var_t\left[r_{t+1}^a\right] = \gamma Cov_t\left[\Delta c_{t+1}, r_{t+1}^a\right] + \gamma Cov_t\left[\Delta s_{t+1}, r_{t+1}^a\right] \tag{6.32}$$

where $r_{t+1}^a = logR_{t+1}^a$, $r_{t+1}^f = logR_{t+1}^f$, $\Delta c_{t+1} = log\frac{C_{t+1}}{C_t}$, and $\Delta s_{t+1} = log\frac{S_{t+1}}{S_t}$. Since $\frac{dC^I}{C^I} \propto \frac{d\kappa^I}{\kappa^I}$ and $\Delta s_{t+1} = -log\left(\frac{\gamma/S_{t+1}}{\gamma/S_t}\right) = -log\left(\frac{\Gamma_{t+1}}{\Gamma_t}\right) \propto -\Delta\left(\frac{\kappa_{t+1}^H - \kappa_{t+1}^L}{\kappa_{t+1}}\right)$, Equation (6.32) is further approximated to

$$E_t\left[r_{t+1}^a - r_{t+1}^f\right] \approx \lambda^{LEVEL}\underbrace{Cov_t\left[\Delta\kappa_{t+1}, r_{t+1}^a\right]}_{\text{Shock in Level of Capital}} - \lambda^{DISP}\underbrace{Cov_t\left[\Delta\left(\frac{\kappa_{t+1}^H - \kappa_{t+1}^L}{\kappa_{t+1}}\right), r_{t+1}^a\right]}_{\text{Shock in Dispersion of Capital}} \tag{6.33}$$

[29] Equation (6.25) can be rewritten using these relations,

$$\frac{1}{\Gamma_t} = \frac{C_t - X_t}{\gamma C_t} = \frac{C_t^H}{C_t}\frac{C_t^H - X_t^H}{\gamma C_t^H} + \frac{C_t^L}{C_t}\frac{C_t^L - X_t^L}{\gamma C_t^L} = \frac{\left(M_t/\xi^H e^{-\rho t}\right)^{-\frac{1}{\gamma}}}{\gamma C_t} + \frac{\left(M_t/\xi^L e^{-\rho t}\right)^{-\frac{1}{\gamma}}}{\gamma C_t}$$
$$\Leftrightarrow C_t - X_t = \left(M_t/\xi^H e^{-\rho t}\right)^{-\frac{1}{\gamma}} + \left(M_t/\xi^L e^{-\rho t}\right)^{-\frac{1}{\gamma}} = \left[\left(\xi^H\right)^{\gamma} + \left(\xi^H\right)^{\gamma}\right]\left(M_t/e^{-\rho t}\right)^{-\frac{1}{\gamma}}$$
$$\Leftrightarrow M_t = \left[\left(\xi^H\right)^{\frac{1}{\gamma}} + \left(\xi^H\right)^{\frac{1}{\gamma}}\right]^{\gamma} e^{-\rho t}\left(C_t - X_t\right)^{-\gamma}.$$

[30] Taking logarithms of each side,

$$E_t\left[-\rho - \gamma log\left(\frac{C_{t+1}}{C_t}\right) - \gamma log\left(\frac{S_{t+1}}{S_t}\right) + logR_{t+1}^a\right]$$
$$+\frac{\gamma^2}{2}Var_t\left[log\left(\frac{C_{t+1}}{C_t}\right)\right] + \frac{\gamma^2}{2}Var_t\left[log\left(\frac{S_{t+1}}{S_t}\right)\right] + \gamma^2 Cov_t\left[log\left(\frac{C_{t+1}}{C_t}\right), log\left(\frac{S_{t+1}}{S_t}\right)\right]$$
$$+\frac{1}{2}Var_t\left[logR_{t+1}^a\right] - \gamma Cov_t\left[log\left(\frac{C_{t+1}}{C_t}\right), logR_{t+1}^a\right] - \gamma Cov_t\left[log\left(\frac{S_{t+1}}{S_t}\right), logR_{t+1}^a\right] = 0$$

For the risk-free asset,

$$E_t\left[-\rho - \gamma log\left(\frac{C_{t+1}}{C_t}\right) - \gamma log\left(\frac{S_{t+1}}{S_t}\right) + logR_{t+1}^f\right]$$
$$+\frac{\gamma^2}{2}Var_t\left[log\left(\frac{C_{t+1}}{C_t}\right)\right] + \frac{\gamma^2}{2}Var_t\left[log\left(\frac{S_{t+1}}{S_t}\right)\right] + \gamma^2 Cov_t\left[log\left(\frac{C_{t+1}}{C_t}\right), log\left(\frac{S_{t+1}}{S_t}\right)\right] = 0.$$

The difference between two equations results in Equation (6.32).

where $\lambda^{LEVEL} > 0$ and $\lambda^{DISP} > 0$ capture the prices of the risks from the shock in level of capital and the shock in dispersion of capital. Thus, the risk premium is determined by the compensation for the exposure to the shock in the dispersion of capital (λ^{DISP}) in addition to the shock in the level of capital (λ^{LEVEL}). Empirically, the negative sign for λ^{DISP} in (6.33) corresponds to the negative price of risk for λ^{DISP} in the asset pricing tests of (4.1).

6.5 Calibration

Now, I present a numerical example to provide quantitative implications of the model presented in previous subsections. In this calibration, I focus on the most realistic situation in Section 6.3, where inequality constraints in (6.15) and (6.16) are slack.

Parameters used to calibrate are described in Table 14 Panel A. First, the unconditional mean and volatility of the risky asset and the risk-free rate are chosen to match the data in the post-war period. In detail, annualized value-weighted returns and volatilities on S&P 500 from January 1950 to December 2016 were roughly 10% and 14% on average. The annualized one-monthly Treasury Bill rate during the same period approaches 4%. Thus, I set $\mu = 10\%$, $\sigma = 16\%$, and $r^f = 4\%$. Second, the initial endowment of all agents, including the two specialists (e^H and e^L) and the household (e^{hh}), is assumed to be 100, and their time preference (ρ) is supposed to be 0.05. Third, in the specialists' utility function, I use a curvature parameter $\gamma = 2$ following Campbell and Cochrane (1999). Specialists' risk aversion is driven by a habit process, X_t^I in (6.7), which is a function of common habit persistence (η), and heterogeneous habit persistence (ϕ^H and ϕ^L). I choose $\eta = 0.95$, $\phi^H = 0.9$, and $\phi^L = 0.1$ so that specialist H has higher risk aversion than specialist L. Fourth, the risk aversion of the household (A) is set to be 3, so as to make the household have higher risk aversion than specialist L but lower risk aversion than specialist H. This choice is not sensitive to key outcomes of the model since the household is restricted to directly invest in the risky asset. Finally, unconditional mean (g) and volatility (σ_c) of consumption are chosen to be 2%.

Based on these parameters, I run a random sampling of a shock (ε_t) in the economy at $t \in \{1, 2\}$, which drives both the return on the risky asset and the consumption growth, from the *i.i.d.* normal distribution. I repeat this exercise 10,000 times to obtain conditional moments.

Table 14 Panel B documents the outcomes of the calibration. All moments are measured at

$t = 1$. The baseline outcomes in the first column are based on the parameters described in Panel A. The model produces a risk premium of 8.44%. More importantly, if I decompose the risk premium as in Equation (6.33), the risk premium due to the capital level is only 2.47%, but the dispersion of intermediary capital generates an additional risk premium of 5.97%. Furthermore, the risk aversion of specialist H ($\Gamma^H = 12.50$) is more than 5 times greater than the risk aversion of specialist L ($\Gamma^L = 2.21$). Consistent with the risk aversion, specialist L ($\alpha^L = 2.08$) has a higher leverage than specialist H ($\alpha^H = 0.37$). The capital of intermediary H ($\kappa^H = 105.0$) is almost twice the capital of intermediary L ($\kappa^L = 52.6$). The moments reported in this column are consistent with the argument of the model as well as the empirical findings in Figure 1 and Table 2: a risk-averse (risk-tolerant) specialist develops a high- (low-) capital intermediary and holds less risky (riskier) portfolio.

In the remaining columns in Panel B, I change the value of ϕ^H and ϕ^L, γ, A, or η one at a time while keeping the other parameters constant to examine how the baseline outcome varies accordingly. First, relative to the baseline model, I lower the habit persistence of specialist H and raise that of specialist L to reduce the degree of heterogeneity in habit persistence (i.e., $(\phi^H, \phi^L) = (0.6, 0.3)$). As shown in the second column, the changes in ϕ^H and ϕ^L lead to a decline in the degree of heterogeneity in risk aversion between two specialists; the risk aversion of specialist H is only 1.5 times greater than that of specialist L (4.54 versus 2.78). Interestingly, this is not accompanied with a lower risk premium; the risk premium increases to 11.79%. Specialist H now requires a lower premium on the risky asset but raises its leverage instead, thereby increasing the specialist H's proportion in the risky asset market from 26.2% to 56.9%.[31] The resulting increase in aggregate risk aversion may explain the higher risk premium than that in the baseline model.

Second, since γ influences decisions of both specialists, lowering γ to 1 reduces the risk aversion of both specialists by half and doubles the leverage of both specialists, which in turn curtails the risk premium by half. With regard to the household's allocation, as specialists become more risk-tolerant, the household is less willing to purchase equity capital of intermediaries. Thus, the capital of both intermediaries is lower than in the baseline model.

Third, as noted earlier, the risk aversion of the household, who is restricted to directly invest in the risky asset, should not matter to the risk premium. Not surprisingly, setting $A = 5$ does not

31 $\frac{0.37\times 105.0}{0.37\times 105.0 + 2.08\times 52.6} \rightarrow \frac{1.01\times 105.0}{1.01\times 105.0 + 1.65\times 48.7}$

affect the conditional moments, except for intermediary capital, in the fourth column. The more risk-averse household now invests less in equity capital of intermediaries but more in the risk-free asset, and this causes total intermediary capital to decline by 27%.

Finally, as η decreases to 0.65, internal habits (X^H and X^L) decreases as well. This leads to a rise in the surplus consumption ratio and a reduction in risk aversion. Similar to the case with $(\phi^H, \phi^L) = (0.6, 0.3)$ in the second column, however, the effect of their lower risk aversion is dampened by the increase in the portion of the specialist H (i.e., α^H), who is more risk-averse, in the risky asset market. Hence, the risk premium rises to 11.79%.

Figure 5 shows the variation in key quantities (e.g., the intermediary capital (κ_2^I), the specialists' consumption (C_2^I), the risk aversion (Γ_2^I) for $I \in \{H, L\}$, and the aggregate risk aversion) in each outcome for a shock at $t = 2$. In Panel (a), as a positive shock hits the economy, capital of both intermediaries grows, but the higher leverage of intermediary L makes the capital of the intermediary L grow faster than that of intermediary H, which generates the negative relation between the shock and dispersion of intermediary capital in (6.26). If the shock is greater than about one standard deviation above the mean of zero, the capital of the intermediary L exceeds that of the intermediary H, and then the dispersion of intermediary capital turns negative. As expected, the shock has a similar effect on the specialists' consumption as shown in Panel (b), and this confirms the inverse relation between the shock and dispersion of specialists' consumption in (6.27).

Panel (c) confirms the notion that the habit makes agents more (less) risk-averse during bad (good) times. More importantly, aggregate risk aversion approaches the risk aversion of specialist H during bad times ($\varepsilon < 0$) and the risk aversion of specialist L during good times ($\varepsilon > 0$) since the aggregate risk aversion is determined by the consumption weights of the specialists (and their risk aversion). Finally, combining Panels (b) and (c) leads to the key implication of the model: dispersion of intermediary capital is positively associated with the aggregate risk aversion of the market, as shown in (6.29).

7 Conclusion

This paper studies how heterogeneity in intermediary capital, measured as the dispersion of the market capital ratio of the largest 30 intermediaries in the U.S., affects the cross-section of stock returns. I posit that the heterogeneity in intermediary capital would capture the countercyclical variation in aggregate risk aversion, which elicits the countercyclical risk premium accordingly. The exposure (i.e., beta) of nonfinancial stocks to shock in the dispersion of capital ratios generates an annual premium of 6.8% - 8.2%. Using the Thomson Reuters Institutional (13F) Holdings database, I also find evidence that low-capital intermediaries, who hold riskier assets than high-capital intermediaries, would face leverage-induced fire-sales once a sufficiently large and systematic adverse shock arrives in stock markets. I develop a model of heterogeneous intermediary capital in which the dispersion of intermediary capital is priced in the cross-section of asset prices, which supports the empirical findings.

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A Appendix

A.1 Proofs

Proof of Proposition 1. Equation (6.10) implies that $\Gamma_1^H = \frac{\gamma}{S_1^H}$ and $\Gamma_1^L = \frac{\gamma}{S_1^L}$. From (6.7) and $\Delta c_1 = g + \sigma_c \varepsilon_1$, the surplus consumption ratio of specialist H (S_1^H) is lower than that of specialist L (S_1^L) at $t = 1$:

$$S_1^H = \frac{C_1^H - X_1^H}{C_1^H} = 1 - \eta\phi^H \frac{C_0^H}{C_1^H} < S_t^L = \frac{C_t^L - X_1^L}{C_1^L} = 1 - \eta\phi^L \frac{C_0^L}{C_1^L}. \tag{A.1}$$

Thus, specialist H has higher risk aversion than specialist L at $t = 1$, or $\Gamma_1^H > \Gamma_1^L$.

In addition, a more risk-averse specialist will require higher risk premium (i.e., expected return) against per unit risk (i.e., variance) for her portfolio than a risk-tolerant specialist. This implies that:

$$\frac{E_1\left[r_2^H - r_2^f\right]}{Var_1\left(r_2^H\right)} = \frac{\alpha_1^H E_1\left[r_2^a - r_2^f\right]}{\left(\alpha_1^H\right)^2 Var_1\left(r_2^a\right)} > \frac{E_1\left[r_2^L - r_2^f\right]}{Var_1\left(r_2^L\right)} = \frac{\alpha_1^L E_1\left[r_2^a - r_2^f\right]}{\left(\alpha_1^L\right)^2 Var_1\left(r_2^a\right)}. \tag{A.2}$$

Therefore, specialist L allocates a higher portion of her wealth into the risky asset than specialist H at $t = 1$, or $\alpha_1^H < \alpha_1^L$. ■

Proof of Proposition 2. From the first order conditions of (6.18) and (6.19), $E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right] = 0$ or, equivalently, $\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L = \frac{1}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}$. Let $Y_t \equiv \frac{1}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}$. Using (6.15), I obtain that

$$\psi_t^L = \frac{Y_t - \alpha_t^H\psi_t^H}{\alpha_t^L} \geq \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - \psi_t^H \quad \text{and} \quad \psi_t^H = \frac{Y_t - \alpha_t^L\psi_t^L}{\alpha_t^H} \geq \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - \psi_t^L.$$

If further rearranged, then

$$\psi_t^H \geq \frac{\alpha_t^L \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\alpha_t^L - \alpha_t^H} \quad \text{and} \quad \psi_t^L \leq \frac{Y_t - \alpha_t^H \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}}{\alpha_t^L - \alpha_t^H}. \tag{A.3}$$

When the minimum capital $\tilde{\kappa}^* \equiv \frac{2}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}\frac{w_t^{hh}}{\alpha_t^H + \alpha_t^L} + \left(w_t^H + w_t^L\right)$, the household's allocation is that:

$$\psi_t^{H*} \geq \frac{\alpha_t^L \frac{\tilde{\kappa}^* - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\alpha_t^L - \alpha_t^H)} = \frac{\alpha_t^L \frac{2Y_t}{\alpha_t^L + \alpha_t^H} - Y_t}{\alpha_t^L - \alpha_t^H} = \frac{Y_t}{\alpha_t^L + \alpha_t^H}$$

$$\psi_t^{L*} \leq \frac{Y_t - \alpha_t^H \frac{\tilde{\kappa}^* - w_t^H - w_t^L}{w_t^{hh}}}{\left(\alpha_t^L - \alpha_t^H\right)} = \frac{Y_t - \alpha_t^H \frac{2Y_t}{\alpha_t^L + \alpha_t^H}}{\alpha_t^L - \alpha_t^H} = \frac{Y_t}{\alpha_t^L + \alpha_t^H}.$$

Thus, if $\tilde{\kappa} > \tilde{\kappa}^*$, $\psi_t^H > \psi_t^L$, that is the household purchases more equity capital from intermediary H than from intermediary L. ■

Proof of Proposition 3. From (6.9), $\partial C_0^I / \partial \phi^I < 0$, $C_0^H < C_0^L$ and $C_1^H < C_1^L$, and from (6.6), $w_1^I = \left(e^I - C_0^I\right)\left(1 + r_1^I\right) - C_1^I$. This implies that specialist H has larger wealth to form an intermediary than specialist L at $t = 1$, or $w_1^H > w_1^L$. Combined with Proposition 2 that if $\tilde{\kappa} > \tilde{\kappa}^*$, $\psi_t^H > \psi_t^L$, the following inequality holds:

$$\kappa_1^H = w_1^H + \psi_1^H w_1^{hh} > \kappa_1^L = w_1^L + \psi_t^L w_1^{hh}. \tag{A.4}$$

Therefore, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^*$, the specialist who has higher (lower) risk aversion forms an intermediary with higher (lower) capital. ■

Proof of Proposition 4. Let me derive the percentage change of intermediary capital to the shock at $t = 2$. For specialist H,

$$\begin{aligned}\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} &= \frac{\kappa_1^H\left[1 + r_2^H\right] - E\left[\kappa_1^H\left[1 + r_2^H\right]\right]}{E\left[\kappa_1^H\left[1 + r_2^H\right]\right]} \\ &= \frac{\kappa_1^H\left[1 + \alpha_1^H\left(r_2^a - r_2^f\right) + r_2^f\right] - E\left[\kappa_1^H\left[1 + \alpha_1^H\left(r_2^a - r_2^f\right) + r_2^f\right]\right]}{E\left[\kappa_1^H\left[1 + \alpha_1^H\left(r_2^a - r_2^f\right) + r_2^f\right]\right]} = \frac{\alpha_1^H \sigma_2 \varepsilon_2}{1 + \alpha_1^H\left(\mu_2 - r_2^f\right) + r_2^f}.\end{aligned}$$

Similarly, for specialist L, $\frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} = \frac{\alpha_1^L \sigma_2 \varepsilon_2}{1 + \alpha_1^L\left(\mu_2 - r_2^f\right) + r_2^f}$. Therefore, the difference in their responses is that:

$$\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} = \frac{\alpha_1^H \sigma_2 \varepsilon_2}{1 + \alpha_1^H\left(\mu_2 - r_2^f\right) + r_2^f} - \frac{\alpha_1^L \sigma_2 \varepsilon_2}{1 + \alpha_1^L\left(\mu_2 - r_2^f\right) + r_2^f}$$

$$= \frac{\alpha_1^H \sigma_2 \varepsilon_2 \left[1 + \alpha_1^L\left(\mu_2 - r_2^f\right) + r_2^f\right] - \alpha_1^L \sigma_2 \varepsilon_2 \left[1 + \alpha_1^H\left(\mu_2 - r_2^f\right) + r_2^f\right]}{\left[1 + \alpha_1^H\left(\mu_2 - r_2^f\right) + r_2^f\right]\left[1 + \alpha_1^L\left(\mu_2 - r_2^f\right) + r_2^f\right]}$$

$$= \frac{\sigma_2 \varepsilon_2 \left(\alpha_1^H - \alpha_1^L\right)\left(1 + r_2^f\right)}{\left[1 + \alpha_1^H\left(\mu_2 - r_2^f\right) + r_2^f\right]\left[1 + \alpha_1^L\left(\mu_2 - r_2^f\right) + r_2^f\right]}$$

Consequently, when $\varepsilon_2 > 0$, $\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} < 0$, and when $\varepsilon_2 < 0$, $\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} > 0$. This is summarized as follows:

$$\varepsilon_2 \left(\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]}\right) < 0 \tag{A.5}$$

Note that a consumption function is a monotonic transformation of wealth. Thus, $\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} = \frac{w_2^H - E\left[w_2^H\right]}{E\left[w_2^H\right]} - \frac{w_2^L - E\left[w_2^L\right]}{E\left[w_2^L\right]} \propto \frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} - \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]}$. This results in the following relationship between the shock in the risky asset and the dispersion in consumption changes between the two specialists.

$$\varepsilon_2 \left(\frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} - \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]}\right) < 0 \tag{A.6}$$

■

Proof of Proposition 5. First, I prove that if a negative shock arrives in the risky asset, $\varepsilon_2 < 0$, then aggregate risk aversion rises:

$$\text{If } \varepsilon_2 < 0, \text{ then } \frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} > \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]}$$

$$
\begin{aligned}
\Leftrightarrow\quad & E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) > E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right)\\
\Leftrightarrow\quad & \left\{E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) - E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right)\right\}\frac{1}{\Gamma_2^L}\\
>\quad & \left\{E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) - E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right)\right\}\frac{1}{\Gamma_2^H}\\
\Leftrightarrow\quad & \left\{\begin{array}{c} E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) - \left(E\left[C_2\right] - E\left[C_2^L\right]\right)\left(C_2^L - E\left[C_2^L\right]\right)\\ +E\left[C_2\right]E\left[C_2^L\right] - E\left[C_2\right]E\left[C_2^L\right]\end{array}\right\}\frac{1}{\Gamma_2^L}\\
>\quad & \left\{\begin{array}{c} \left(E\left[C_2\right] - E\left[C_2^H\right]\right)\left(C_2^H - E\left[C_2^H\right]\right) - E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right)\\ +E\left[C_2\right]E\left[C_2^H\right] - E\left[C_2\right]E\left[C_2^H\right]\end{array}\right\}\frac{1}{\Gamma_2^H}\\
\Leftrightarrow\quad & \left\{\begin{array}{c} E\left[C_2^L\right]\left(E\left[C_2\right] + C_2^H - E\left[C_2^H\right] + C_2^L - E\left[C_2^L\right]\right)\\ -\left(E\left[C_2^L\right] + C_2^L - E\left[C_2^L\right]\right)E\left[C_2\right]\end{array}\right\}\frac{1}{\Gamma_2^L}\\
>\quad & \left\{\begin{array}{c} -E\left[C_2^H\right]\left(E\left[C_2\right] + C_2^H - E\left[C_2^H\right] + C_2^L - E\left[C_2^L\right]\right)\\ +\left(E\left[C_2^H\right] + C_2^H - E\left[C_2^H\right]\right)E\left[C_2\right]\end{array}\right\}\frac{1}{\Gamma_2^H}\\
\Leftrightarrow\quad & \left(E\left[C_2^L\right]C_2 - C_2^L E\left[C_2\right]\right)\frac{1}{\Gamma_2^L} > \left(-E\left[C_2^H\right]C_2 + C_2^H E\left[C_2\right]\right)\frac{1}{\Gamma_2^H}\\
\Leftrightarrow\quad & E\left[C_2^H\right]C_2\frac{1}{\Gamma_2^H} + E\left[C_2^L\right]C_2\frac{1}{\Gamma_2^L} > C_2^H E\left[C_2\right]\frac{1}{\Gamma_2^H} + C_2^L E\left[C_2\right]\frac{1}{\Gamma_2^L}\\
\Leftrightarrow\quad & \frac{E\left[C_2^H\right]}{E\left[C_2\right]}\frac{1}{\Gamma_2^H} + \frac{E\left[C_2^L\right]}{E\left[C_2\right]}\frac{1}{\Gamma_2^L} > \frac{C_2^H}{C_2}\frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2}\frac{1}{\Gamma_2^L} \qquad \left(use\ \Gamma_2^I > E\left[\Gamma_2^I\right]\right)\\
\Leftrightarrow\quad & \frac{E\left[C_2^H\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]}\frac{1}{E\left[\Gamma_2^H\right]} + \frac{E\left[C_2^L\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]}\frac{1}{E\left[\Gamma_2^L\right]} > \frac{C_2^H}{C_2^H + C_2^L}\frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2^H + C_2^L}\frac{1}{\Gamma_2^L}
\end{aligned}
$$

where $C \equiv C^H + C^L$ and $E\left[C\right] \equiv E\left[C^H\right] + E\left[C^L\right]$. Therefore, if $\varepsilon_2 < 0$, then

$$
\begin{aligned}
\frac{1}{\Gamma_2} \equiv & \frac{C_2^H}{C_2^H + C_2^L}\frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2^H + C_2^L}\frac{1}{\Gamma_2^L}\\
& < \frac{1}{E\left[\Gamma_2\right]} \equiv \frac{E\left[C_2^H\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]}\frac{1}{E\left[\Gamma_2^H\right]} + \frac{E\left[C_2^L\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]}\frac{1}{E\left[\Gamma_2^L\right]}. \quad \text{(A.7)}
\end{aligned}
$$

On the other hand, if a positive shock arrives in the risky asset, $\varepsilon_2 > 0$, then aggregate risk aversion falls:

$$\frac{1}{\Gamma_2} \equiv \frac{C_2^H}{C_2^H + C_2^L}\frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2^H + C_2^L}\frac{1}{\Gamma_2^L}$$
$$> \frac{1}{E\left[\Gamma_2\right]} \equiv \frac{E\left[C_2^H\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]}\frac{1}{E\left[\Gamma_2^H\right]} + \frac{E\left[C_2^L\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]}\frac{1}{E\left[\Gamma_2^L\right]}. \tag{A.8}$$

Finally, combining (A.7) and (A.8) gives:

$$\varepsilon_2 \Gamma_2 < 0. \tag{A.9}$$

As such, the shock in the risky asset and aggregate risk aversion are inversely related at $t = 2$. ■

Proof of Proposition 6. Proposition 4 implies that the dispersion of intermediary capital and the shock at $t = 2$ is negatively related. More formally, I prove this relation as follows:

$$\begin{aligned}
&\frac{\partial DISP_2^{Capr}}{\partial \varepsilon_2} \\
&= \partial \left\{ \frac{\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] - \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]}{\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] + \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]} \right\} / \partial \varepsilon_2 \\
&= \frac{\left(\kappa_1^H\alpha_1^H - \kappa_1^L\alpha_1^L\right)\sigma_2}{\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] + \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]} \\
&- \frac{\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] - \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]}{\left(\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] + \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]\right)^2}\left(\kappa_1^H\alpha_1^H + \kappa_1^L\alpha_1^L\right)\sigma_2 \\
&= \frac{\sigma_2}{\left(\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] + \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]\right)^2} \\
&\times \left\{ \begin{array}{ll} & \left(\kappa_1^H\alpha_1^H - \kappa_1^L\alpha_1^L\right)\left(\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] + \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]\right) \\ - & \left(\kappa_1^H\alpha_1^H + \kappa_1^L\alpha_1^L\right)\left(\kappa_1^H\left[1 + \alpha_1^H\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right] - \kappa_1^L\left[1 + \alpha_1^L\left(\mu_2 + \sigma_2\varepsilon_2\right) + r_2^f\right]\right) \end{array} \right\}
\end{aligned}$$

$$= \frac{\sigma_2}{\left(\kappa_1^H\left[1+\alpha_1^H\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]+\kappa_1^L\left[1+\alpha_1^L\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]\right)^2}$$
$$\times\left(\kappa_1^H\alpha_1^H\kappa_1^L\left[1+\alpha_1^L\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]-\kappa_1^L\alpha_1^L\kappa_1^H\left[1+\alpha_1^H\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]\right)$$
$$= \frac{\sigma_2}{\left(\kappa_1^H\left[1+\alpha_1^H\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]+\kappa_1^L\left[1+\alpha_1^L\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]\right)^2}$$
$$\times\left[\kappa_1^H\kappa_1^L\left(1+r_2^f\right)\left(\alpha_1^H-\alpha_1^L\right)\right]$$
$$= \frac{\kappa_1^H\kappa_1^L\left(1+r_2^f\right)\sigma_2}{\left(\kappa_1^H\left[1+\alpha_1^H\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]+\kappa_1^L\left[1+\alpha_1^L\left(\mu_2+\sigma_2\varepsilon_2\right)+r_2^f\right]\right)^2}\times\left(\alpha_1^H-\alpha_1^L\right)<0.$$

Together with the countercyclical variation in aggregate risk aversion in Proposition 5, I obtain the following result:

$$\left(\frac{\kappa_2^H-\kappa_2^L}{\kappa_2}\right)\Gamma_2>0. \tag{A.10}$$

At $t=2$, the dispersion of intermediary capital is *positively* associated with the aggregate risk aversion of the market. ■

A.2 Other Cases of the Household Problem in Section 6.3

In this section, I consider the cases where the minimum capital requirement in (6.15) and/or the capital constraints in (6.16) are not slack. That is, at least one of θ_t^C, θ_t^H, and θ_t^L is nonzero.

Case 1: $\theta_t^H>0$ and $\theta_t^L>0$

In this case, capital constraints for both intermediaries hold, so the solution is immediate from (6.21) and (6.22); $\psi_t^H=m\frac{w_t^H}{w_t^{hh}}>\psi_t^L=m\frac{w_t^L}{w_t^{hh}}$. Thus, the household allocates larger wealth to intermediary H than to intermediary L.

Case 2: $\theta_t^H>0$ and $\theta_t^L=0$

I considers the case where the capital constraint for specialist H binds, but that for specialist L does not. If $\theta_t^C=0$, then from Equation (6.19), $E_t\left[r_{t+1}^a-r_{t+1}^f\right]-A\left(\alpha_t^H\psi_t^H+\alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right]=0$. Equation (6.18) implies that $\theta_t^H=0$, so this case does not have a feasible solution. If $\theta_t^C>0$, then

$\psi_t^H = m\frac{w_t^H}{w_t^{hh}}$ from (6.21), and $\psi_t^L = \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - m\frac{w_t^H}{w_t^{hh}}$ from (6.20). Since $\psi_t^L < m\frac{w_t^L}{w_t^{hh}}$ and $m\frac{w_t^H}{w_t^{hh}} > m\frac{w_t^L}{w_t^{hh}}$, I have that $\psi_t^H > \psi_t^L$. Again, the household purchases more equity capital from intermediary H than from intermediary L.

Case 3: $\theta_t^H = 0$ and $\theta_t^L > 0$

Suppose that the capital constraint for specialist L binds, but that for specialist H does not. If $\theta_t^C = 0$, then from Equation (6.18), $E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right] = 0$. From Equation (6.19), $\theta_t^L = 0$, so this case does not have a feasible solution, similar to Case 2. If $\theta_t^C > 0$, then $\psi_t^L = m\frac{w_t^L}{w_t^{hh}}$ from (6.22), and $\psi_t^H = \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - m\frac{w_t^L}{w_t^{hh}}$ from (6.20). There is a minimum capital $\tilde{\kappa}^{**} \equiv 2mw_t^L + \left(w_t^H + w_t^L\right)$ that satisfies $\psi_t^H = \psi_t^L$. Thus, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^{**}$, the household allocates a larger portion of her wealth to intermediary H than to intermediary L (i.e., $\psi_t^H > \psi_t^L$).

Case 4: $\theta_t^H = 0$ and $\theta_t^L = 0$

Finally, I examine the case where capital constraints for both intermediaries does not bind, but the minimum capital requirement binds. Because $\theta_t^C > 0$, (6.18) and (6.19) can be rewritten as follows: $\alpha_t^H E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^H\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right] = \alpha_t^L E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^L\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right]$, which further implies that $\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L = \frac{1}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}$. Next, from (6.20), I obtain that

$$\psi_t^H = \frac{\alpha_t^L\frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\left(\alpha_t^L - \alpha_t^H\right)} \quad \text{and} \quad \psi_t^L = \frac{Y_t - \alpha_t^H\frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}}{\left(\alpha_t^L - \alpha_t^H\right)}.$$

Let $Y_t \equiv \frac{1}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}$. The minimum capital $\tilde{\kappa}^*$, defined in Proposition 2, satisfies $\psi_t^H = \psi_t^L$. Again, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^*$, the household purchases more equity capital from the intermediary H than the intermediary L (i.e., $\psi_t^H > \psi_t^L$).

Table A.1
List of Intermediaries

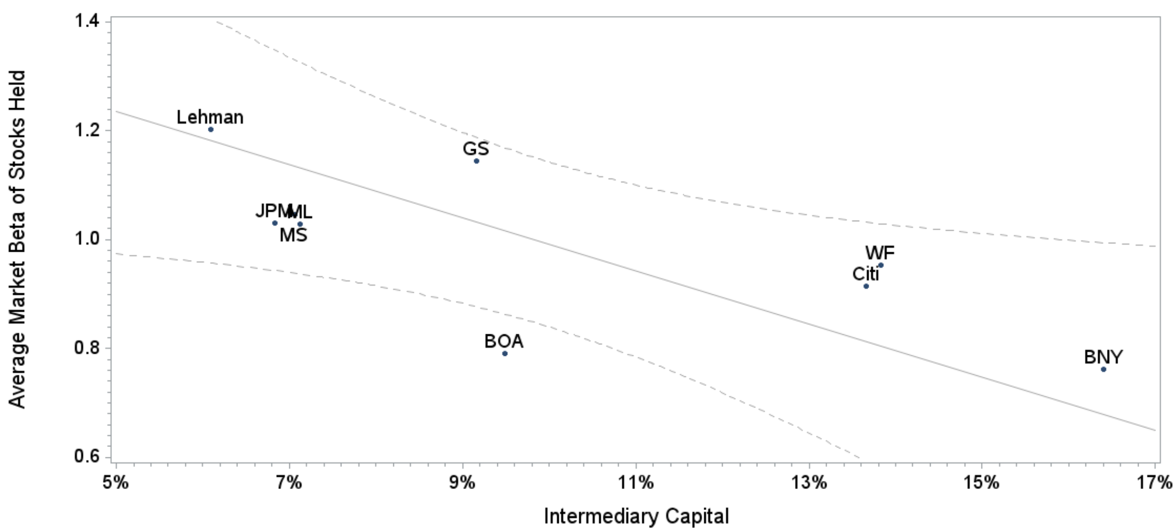
This table lists 118 intermediaries in the sample. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter from 1973/Q1 to 2016/Q4. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6).

Intermediary Name	Intermediary Name	Intermediary Name
AFFILIATED MANAGERS GROUP INC	FEDERAL NATIONAL MORTGAGE ASSN	NEW YORK COMMUNITY BANCORP INC
ALLY FINANCIAL INC	FIRST CHARTER FINL CORP	NORTH FORK BANCORPORATION NY INC
AMERICAN EXPRESS CO	FIRST CHICAGO CORP	NORTHERN TRUST CORP
AMERIPRISE FINANCIAL INC	FIRST CHICAGO N B D CORP	P N C FINANCIAL SERVICES GRP INC
AMERITRUST CORP	FIRST FIDELITY BANCORP	PAINE WEBBER INC
ASSOCIATES FIRST CAPITAL CORP	FIRST INTL BANCSHARES INC	PEOPLES UNITED FINANCIAL INC
B B & T CORP	FIRST PENNSYLVANIA CORP	PROVIDIAN FINANCIAL CORP
BACHE GROUP INC	FIRST REPUBLIC BANK S F	PRUDENTIAL FINANCIAL INC
BANK NEW ENGLAND CORP	FIRST SECURITY CORP DE	REGIONS FINANCIAL CORP
BANK OF AMERICA CORP	FIRST TENNESSEE NATIONAL CORP	REPUBLICBANK CORP
BANK OF NEW YORK MELLON CORP	FIRSTAR CORP	RYDER SYSTEMS INC
BANK ONE CORP	FLEETBOSTON FINANCIAL CORP	S & P GLOBAL INC
BANKAMERICA CORP	FRANKLIN RESOURCES INC	S L M CORP
BANKBOSTON CORP	GOLDEN WEST FINANCIAL CORP	SALOMON INC
BANKERS TRUST CORP	GOLDMAN SACHS GROUP INC	SCHWAB CHARLES CORP
BEAR STEARNS COMPANIES INC	GREAT WESTERN FINANCIAL CORP	SHAWMUT NATIONAL CORP
BLACKROCK INC	HARRIS BANKCORP INC	SHEARSON LOEB RHOADES INC
BLOCK H & R INC	HOUSEHOLD INTERNATIONAL INC	SOCIETY CORP
C & S SOVRAN CORP	HUDSON CITY BANCORP INC	SOUTHTRUST CORP
C I T GROUP INC	HUTTON E F GROUP INC	SOUTHWEST BANCSHARES INC
C M E GROUP INC	I T T HARTFORD GROUP INC	SOVRAN FINANCIAL CORP
CAPITAL ONE FINANCIAL CORP	INTERCONTINENTALEXCHANGE GRP INC	STATE STREET CORP
CHARTER COMPANY	JPMORGAN CHASE & CO	SUNAMERICA INC
CHARTER NEW YORK CORP	KEYCORP	SUNTRUST BANKS INC
CHASE MANHATTAN CORP	LEGG MASON INC	T D AMERITRADE HOLDING CORP
CITICORP	LEHMAN BROTHERS HOLDINGS INC	T ROWE PRICE GROUP INC
CITIGROUP INC	M & T BANK CORP	TEXAS COMMERCE BANCSHARES INC
CITIZENS & SOUTHERN CORP GA	M B N A CORP	U S BANCORP DEL
CITIZENS FINANCIAL GROUP INC	M CORP	UNION BANCORP INC
COMERICA INC	M N C FINANCIAL INC	UNIONBANCAL CORP
CONCORD E F S INC	MANUFACTURERS HANOVER CORP	UNITED VIRGINIA BANKSHARES INC
CONTINENTAL ILL CORP	MARINE MIDLAND BKS INC	VALLEY NATIONAL CORP AZ
CORESTATES FINANCIAL CORP	MELLON FINANCIAL CORP	VISA INC
COUNTRYWIDE FINANCIAL CORP	MERCANTILE BANCORPORATION INC	WACHOVIA CORP
CROCKER NATIONAL CORP	MERRILL LYNCH & CO INC	WACHOVIA CORP NEW
DEAN WITTER DISCOVER & CO	MORGAN STANLEY DEAN WITTER & CO	WASHINGTON MUTUAL INC
DISCOVER FINANCIAL SERVICES	N Y S E EURONEXT	WELLS FARGO & CO
DREYFUS CORP	NASDAQ INC	WELLS FARGO & CO NEW
FEDERAL HOME LOAN MORTGAGE CORP	NATIONAL CITY CORP	WESTERN BANCORPORATION
		WESTERN UNION CO

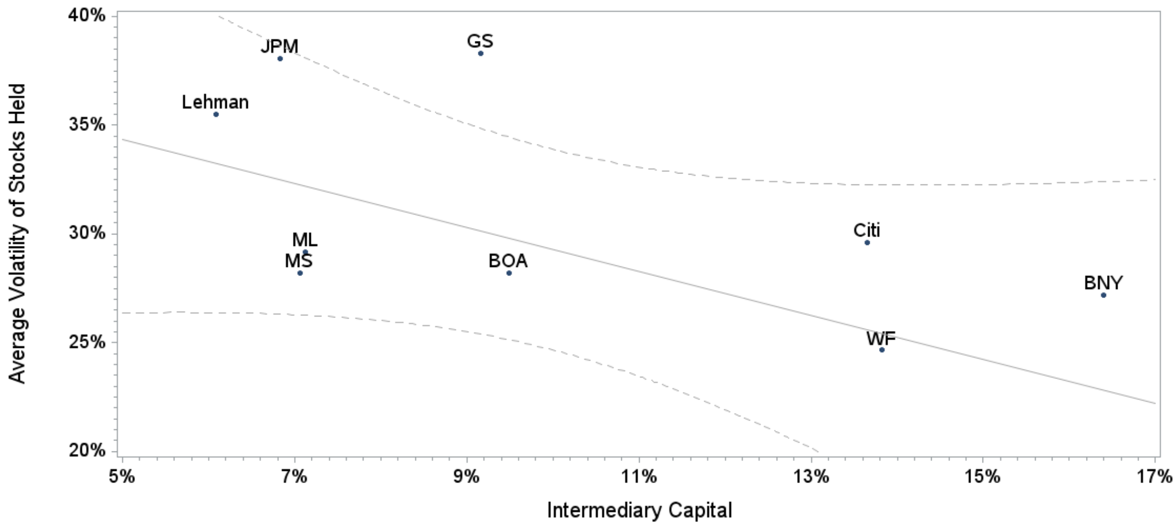
Figure 1
Intermediary Capital and Risk Preference

This figure depicts the relation between intermediary capital of the largest 9 intermediaries in the U.S. and three risk characteristics of the nonfinancial firm stocks they hold. The 9 intermediaries include *Bank of America*, *Bank of New York Mellon*, *Citigroup*, *Goldman Sachs*, *JP Morgan Chase*, *Lehman Brothers*, *Merrill Lynch*, *Morgan Stanley*, and *Wells Fargo & Company*. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The risk characteristics are: market beta, estimated from monthly regressions using 5-year rolling windows (Panel A); stock return volatility, defined as the quarterly standard deviation of daily stock returns (Panel B); and the log of market capitalization, the number of shares outstanding times the share price (Panel C). At the end of each quarter, risk characteristics are averaged within each intermediary and then averaged over the sample period. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The solid line represents the fitted regression line, and two dashed lines represent the 95% confidence limits. The sample period covers 1980/Q1 to 2012/Q4.

Panel A: Average Market Beta of Stock Held



Panel B: Average Volatility of Stock Held



Panel C: Average Market Cap of Stock Held

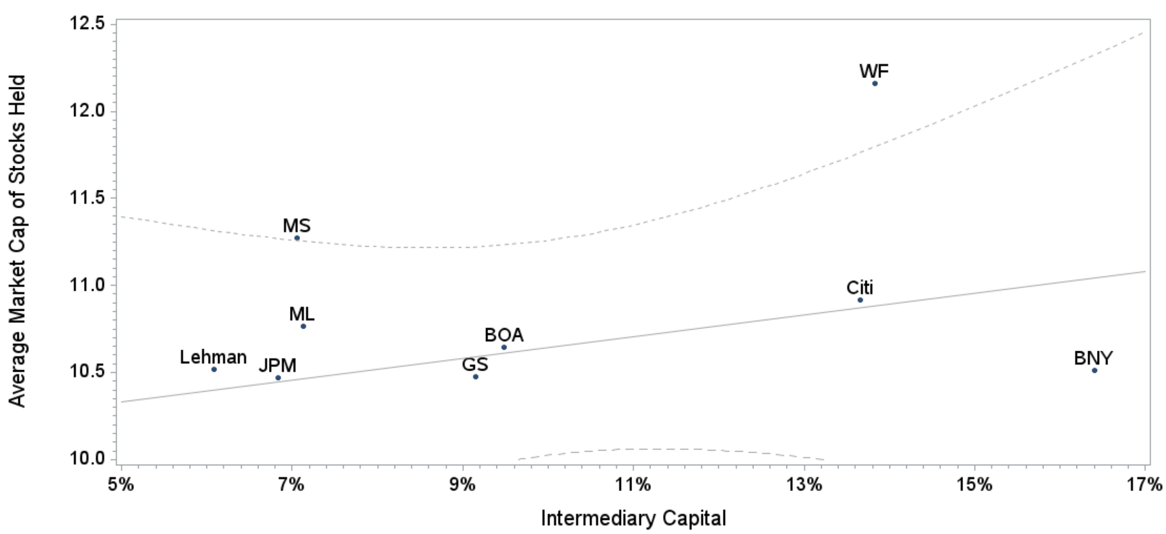
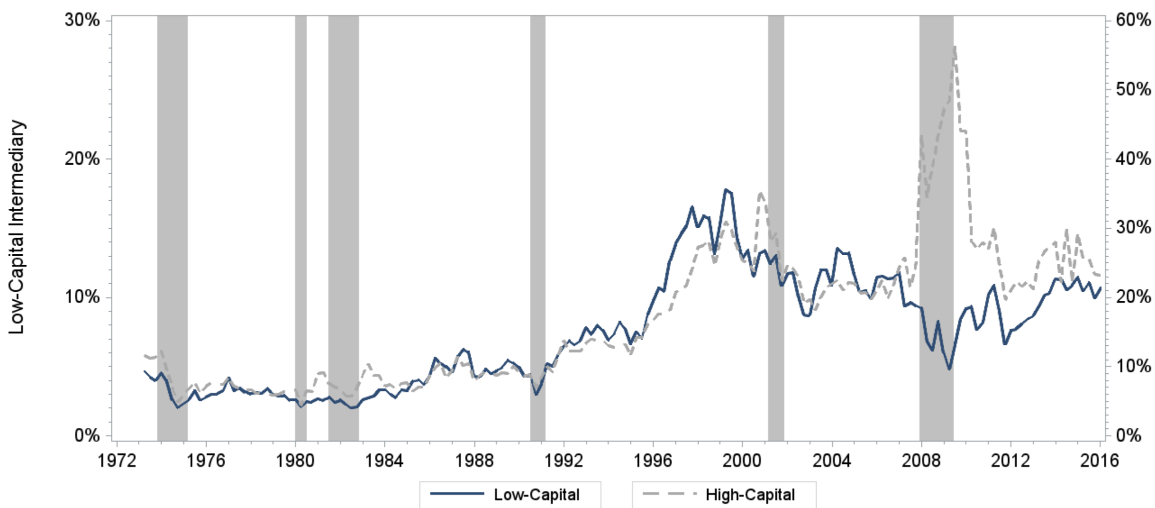


Figure 2

Level and Dispersion of Intermediary Capital Ratio

This figure depicts intermediary capital of the largest 30 intermediaries in the U.S. Panel A plots the level of intermediary capital. The dashed line represents the 75^{th} percentile of intermediary capital while the solid line represents the 25^{th} percentile of intermediary capital. Panel B plots the dispersion of intermediary capital, measured as the difference between the 75^{th} and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile, in the solid line. The change in the dispersion of intermediary capital is shown by the dashed line. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The shaded areas represent NBER recessions. The sample period covers 1973/Q1 to 2016/Q4.

Panel A: Capital Ratios of High- and Low-Capital Intermediaries



Panel B: Dispersion of Intermediary Capital Ratios

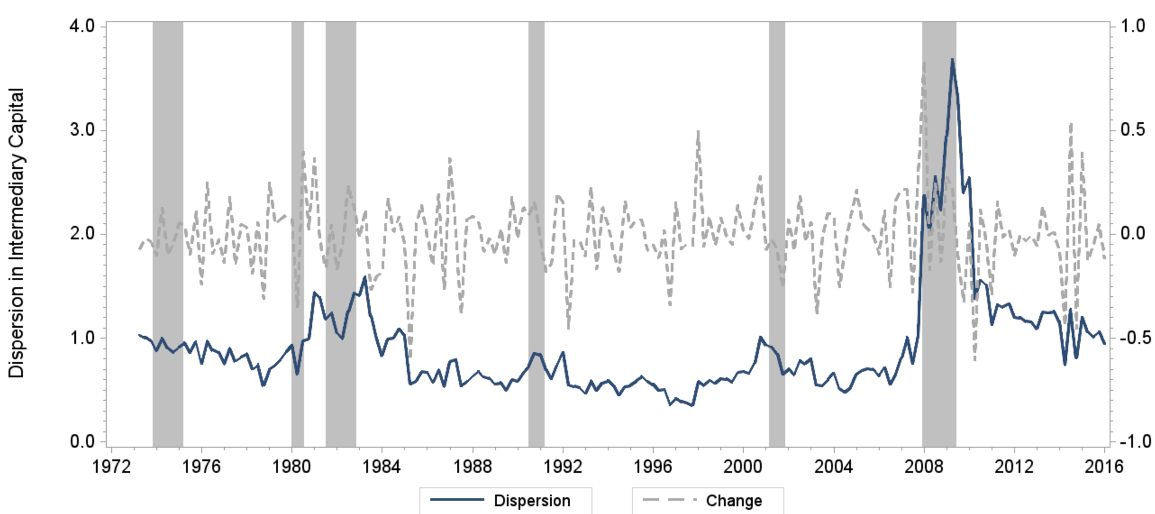
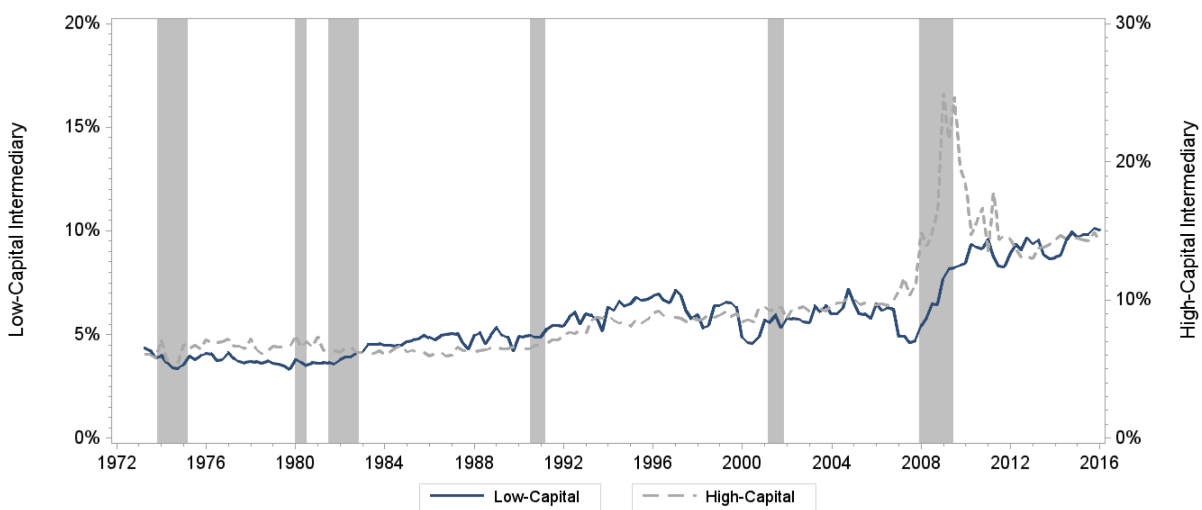


Figure 3

Level and Dispersion of Intermediary Capital Ratios: Book Capital Ratio

This figure depicts intermediary capital of the largest 30 intermediaries in the U.S. Panel A plots the level of intermediary capital. The dashed line represents the 75^{th} percentile of intermediary capital while the solid line represents the 25^{th} percentile of intermediary capital. Panel B plots the dispersion of intermediary capital, measured as the difference between the 75^{th} and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile, in the solid line. The change in the dispersion of intermediary capital is shown by the dashed line. Intermediary capital is measured using the book capital ratio, that is, the book value of equity over the sum of the book value of debt and the book value of equity. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The shaded areas represent NBER recessions. The sample period covers 1973/Q1 to 2016/Q4.

Panel A: Capital Ratios of High- and Low-Capital Intermediaries



Panel B: Dispersion of Intermediary Capital Ratios

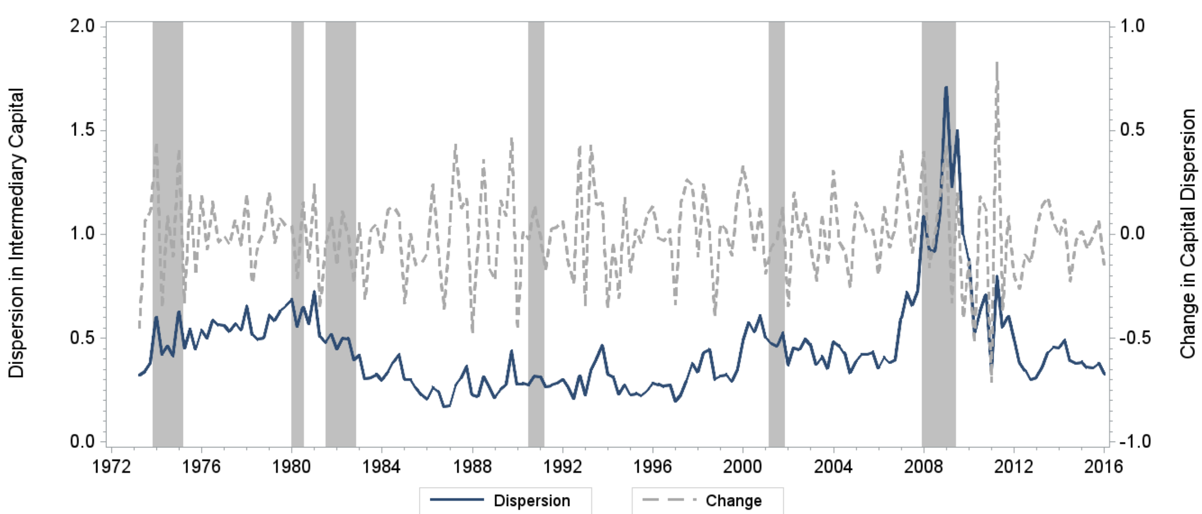


Figure 4
Timeline of Economy

This figure depicts the timeline of the economy described in the model. There are three agents: two specialists $I \in \{H, L\}$ and a household hh. The amount of wealth (w_0^I) and capital (κ_1^I) available to invest by specialists and intermediaries, respectively, is indicated above the timeline. The growth of wealth (w_0^I) and capital (κ_1^I) is displayed below the timeline. At $t = 0$, the specialists arrive in the market with an endowment of e^I and consume C_0^I. At $t = 1$, the household arrives in the market with an endowment of e^{hh} and consumes C_1^{hh}. After consuming C_1^I at $t = 1$, the specialists form intermediaries using their post-consumption wealth of $w_1^I = w_0^I \times (1 + r_1^I) - C_1^I$ plus the household's contribution of $\psi_1^I w_1^{hh}$, where $w_1^{hh} = e^{hh} - C_1^{hh}$. Intermediary capital at $t = 1$, $\kappa_1^I = w_1^I + \psi_1^I w_1^{hh}$, grows to $\kappa_2^I = \kappa_1^I \times (1 + r_2^I)$, where r_2^I is a return on investment at $t = 2$. κ_2^I is distributed and consumed by all agents at their respective ratios.

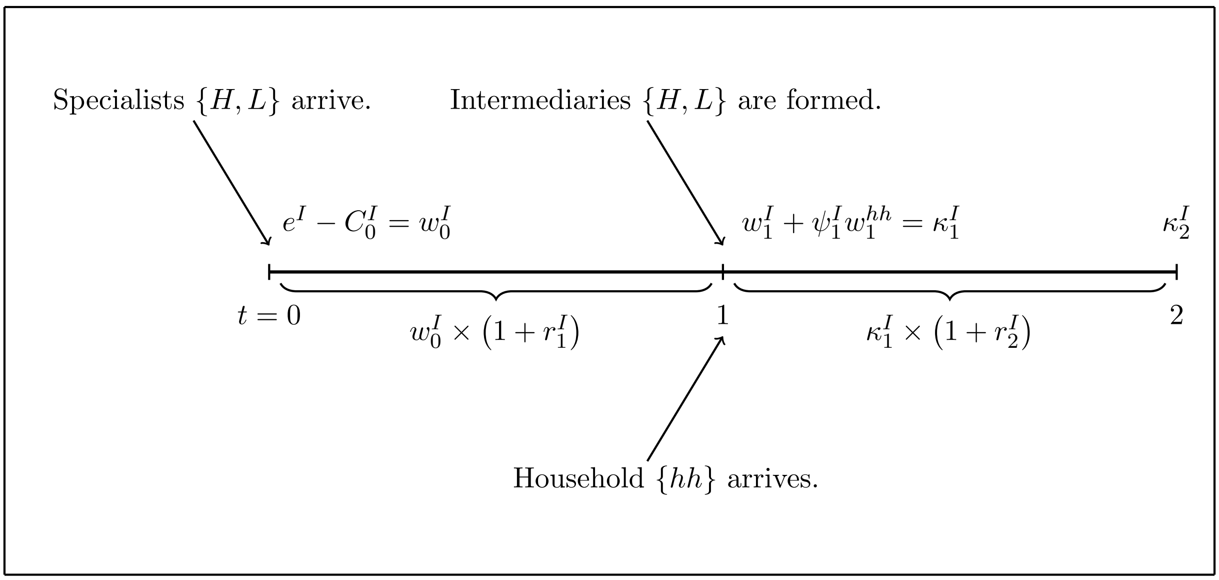
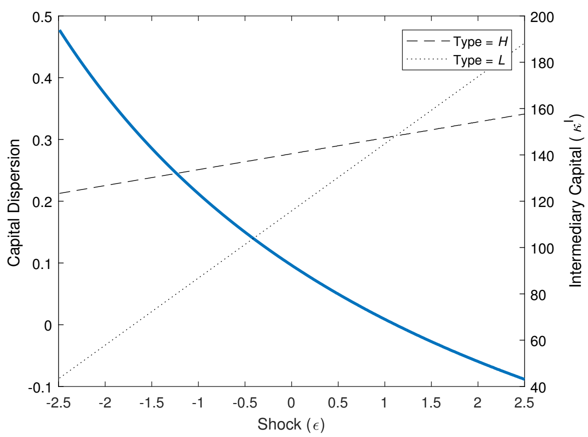


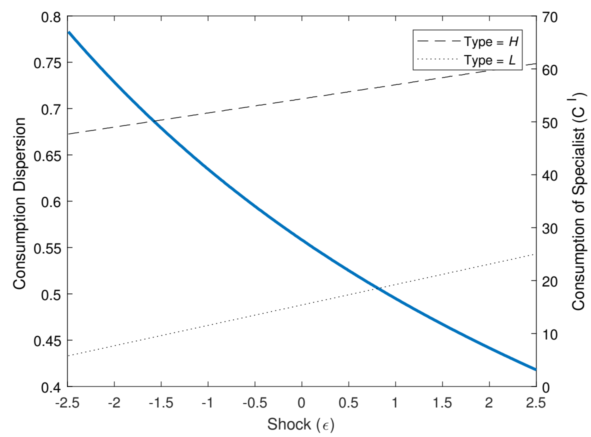
Figure 5
Calibration

This figure depicts the intermediary capital (κ_2^I), specialists' consumption (C_2^I), and the their risk aversion (Γ_2^I) for $I \in \{H, L\}$ as well as the aggregate risk aversion, implied by the model. Panel (a) indicates the relation in (5.33); Panel (b) indicates the relation in (5.34); Panel (c) indicates the relation in (5.37); and Panel (d) indicates the relation in (5.38). In Panels (a) and (b), the solid line represents the dispersion of intermediary capital and specialists' consumption. In Panel (c), the solid line represents the aggregate risk aversion of the economy. In Panels (a) - (c), the dashed line represents quantities of the specialist/intermediary H while the dotted line represents quantities of the specialist/intermediary L. To simulate the economy, I generate a random draw from the $i.i.d.$ normal distribution for each outcome in a shock at $t = 2$. I repeat this exercise 10,000 times to compute average quantities represented in vertical axises.

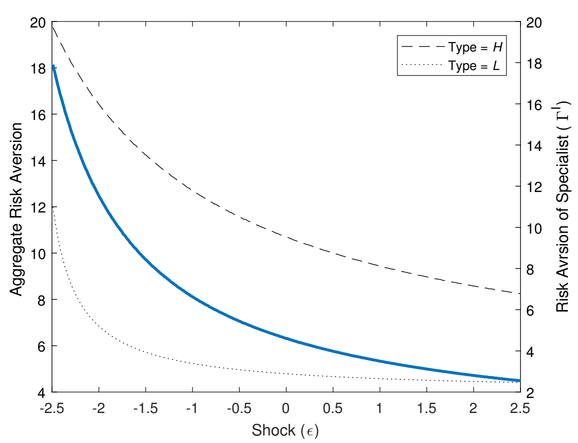
(a)



(b)



(c)



(d)

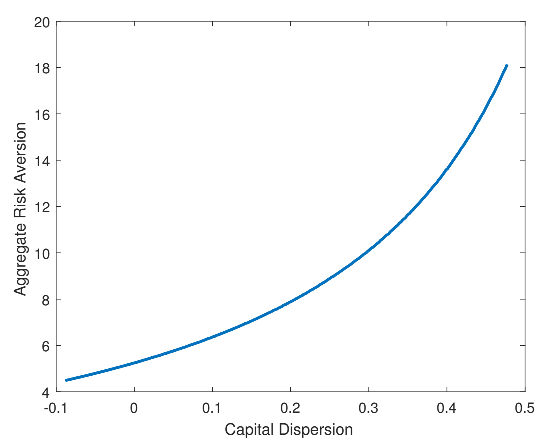


Table 1
Summary Statistics

This table reports the summary statistics. Panel A shows the statistics for intermediaries. At the end of each quarter, the largest 30 intermediaries in the U.S. are sorted into quartiles based on intermediary capital. Panel B shows the statistics for nonfinancial firm stocks. At the beginning of each month, nonfinancial firm stocks are sorted into deciles based on the dispersion beta. The statistics presented in each column indicate the value-weighted averages within each group, which are then averaged over time. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The dispersion beta is defined as

$$\beta^{DISP} = \frac{Cov(\Delta DISP_t^{Capr}, r_t^i)}{Var\left(r_t^i\right)}$$

from quarterly regressions using 5-year rolling windows. r_t^i is a monthly returns on nonfinancial firm stock. $DISP_t^{Capr}$ is the dispersion of intermediary capital measured as the difference between the 75^{th} percentile and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile.

$$DISP_t^{Capr} = \frac{Capr_t^{75^{th}} - Capr_t^{25^{th}}}{Capr_t^{50^{th}}}$$

Capital Ratio (Market) is the quasi-market capital ratio. Capital Ratio (Book) is defined as book equity over total assets. β^{MKT} is the market beta, estimated from monthly regressions using 5-year rolling windows. Market capitalization and book assets (i.e., total assets) are represented in billion dollars. B/M is the book-to-market ratio, book equity over market capitalization. Profitability is measured as ROE, income before extraordinary items over lagged book equity. Asset growth is measured as the percentage change in total assets. Momentum is a cumulative return over the previous one year, skipping the last month. Stock Returns are valued-weighted at the monthly frequency. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1973 to December 2016.

Panel A: Summary Statistics for the Largest 30 Intermediaries by Capital Ratio Quartile

	Low	2	3	High
Capital Ratio (Market)	5.68%	9.24%	13.57%	36.02%
Capital Ratio (Book)	5.43%	6.99%	8.18%	23.57%
β^{MKT}	1.30	1.12	1.10	1.25
Market Cap ($B)	27.83	21.49	20.27	13.27
Book Assets ($B)	380.29	170.38	108.78	33.66
B/M	1.22	0.90	0.69	0.52
Profitability (ROE)	2.82%	3.44%	3.98%	5.99%
Asset Growth (I/A)	3.98%	3.26%	3.97%	4.59%
Momentum	11.40%	14.39%	16.25%	24.00%

Panel B: Summary Statistics for Nonfinancial Firm Stocks by Dispersion Beta Decile

	Low	2	3	4	5	6	7	8	9	High
β^{DISP}	−0.45	−0.21	−0.13	−0.08	−0.03	0.02	0.07	0.12	0.19	0.39
β^{MKT}	1.30	1.14	1.07	1.03	1.00	0.99	0.99	1.00	1.04	1.23
Market Cap ($B)	1.24	2.46	3.06	3.45	3.81	3.91	3.86	3.82	3.12	1.91
Book Assets ($B)	1.23	2.36	2.86	3.10	3.38	3.48	3.43	3.58	3.34	1.95
B/M	0.70	0.74	0.74	0.74	0.73	0.74	0.75	0.75	0.75	0.67
Profitability (ROE)	1.77%	2.19%	2.41%	2.64%	2.68%	2.63%	2.62%	2.63%	2.48%	1.90%
Asset Growth (I/A)	3.39%	2.69%	2.46%	2.52%	2.43%	2.49%	2.56%	2.73%	2.80%	3.62%
Momentum	33.12%	21.55%	19.29%	17.96%	17.58%	17.34%	17.40%	18.08%	18.67%	25.65%
Stock Return	2.67%	2.10%	1.88%	1.69%	1.85%	1.68%	1.78%	1.68%	1.76%	2.08%

Table 2
Risk Preferences of Intermediaries

This table reports the results of OLS regressions in which the risk characteristics of nonfinancial firm stocks held in the largest 30 intermediaries in the U.S. are regressed on the capital ratios of these intermediaries plus controls. Three risk characteristics include: market beta, estimated from monthly regressions using 5-year rolling windows; stock return volatility, defined as the quarterly standard deviation of daily stock returns; and the log of market capitalization, the number of shares outstanding times the share price. Since stocks can be held by multiple intermediaries, intermediary capital and size are averaged within each stock using the number of shares held as a weight. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. Intermediary size is measured as the log of the intermediary's market capitalization. Other controls measured in the stock level include B/M (book-to-market ratio, book equity over market capitalization), MOM (momentum, a cumulative return over the previous one year, skipping the last month), ROE (profitability, income before extraordinary items over lagged book equity), and I/A (asset growth, the percentage change in total assets). The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by stock. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
	β^{MKT}	Return Volatility	Market Cap
Intermediary Capital	-0.129***	-0.019***	0.167***
	[-3.73]	[-3.28]	[3.51]
Intermediary Size	0.020***	-0.001	0.184***
	[3.02]	[-0.95]	[19.42]
B/M	-0.009	-0.143**	0.197
	[-0.33]	[-2.56]	[1.30]
MOM	0.009**	-0.009***	0.232***
	[2.25]	[-10.27]	[24.38]
ROE	0.005	0.004**	0.001
	[0.57]	[2.39]	[0.08]
I/A	-0.020	0.001	0.044
	[-1.15]	[0.22]	[0.78]
Firm FE	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes
N	458,183	458,183	458,183
adj. R^2	0.608	0.532	0.889

Table 3

Countercyclicality in Dispersion of Intermediary Capital Ratios

This table reports the results of OLS regressions showing how the dispersion of intermediary capital changes during bad times. I use two bad time measures: the financial crisis (from July 2007 to December 2009) and NBER recessions. $\mathbb{1}(t = \text{Bad Time})$ is one if month t is in a bad time and zero otherwise. The dispersion of intermediary capital ($DISP^{Capr}$) is measured as the difference between the 75^{th} percentile ($Capr^{75^{th}}$) and the 25^{th} percentile ($Capr^{75^{th}}$) of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The sample period covers 1973/Q1 to 2016/Q4. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Bad Time Def.	*Financial Crisis*			*NBER Recessions*		
	(1)	(2)	(3)	(4)	(5)	(6)
	$DISP^{Capr}$	$Capr^{25^{th}}$	$Capr^{75^{th}}$	$DISP^{Capr}$	$Capr^{25^{th}}$	$Capr^{75^{th}}$
$\mathbb{1}(t = \text{Bad Time})$	1.76***	−0.02*	0.23***	1.06***	−0.02**	0.12***
	[16.09]	[−1.86]	[9.67]	[7.37]	[−2.28]	[4.64]
Intercept	0.75***	0.10***	0.19***	0.79***	0.10***	0.20***
	[24.01]	[30.66]	[28.38]	[16.71]	[30.67]	[23.46]
N	121	121	121	121	121	121
adj. R^2	0.682	0.020	0.436	0.308	0.034	0.146

Table 4

Fama-MacBeth Regressions

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 1, is estimated from quarterly regressions using 5-year rolling windows. β^{MKT} is the market beta, estimated from monthly regressions using 5-year rolling windows. β^{AEM} represents the beta for the intermediary leverage factor in Adrian, Etula, and Muir (2014), and β^{HKM} represents the intermediary capital factor in He, Kelly, and Manela (2017), both estimated from quarterly regressions using 5-year rolling windows. Following Carhart (1997) and Fama and French (2015), I also control for Size (the log of market capitalization), B/M (book-to-market ratio, book equity over market capitalization), MOM (momentum, a cumulative return over the previous one year, skipping the last month), OP (operating profitability, annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by lagged book equity), and I/A (asset growth, the percentage change in total assets). The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.81***	−0.78***	−0.49***	−0.46***	−0.33***	−0.33***	−0.35**
	[−4.25]	[−4.57]	[−3.25]	[−3.49]	[−2.69]	[−2.72]	[−2.55]
β^{MKT}		0.29	0.30*	0.27*	0.30**	0.13	0.20
		[1.61]	[1.71]	[1.83]	[2.00]	[0.98]	[1.28]
β^{AEM}			0.32***		0.15***	0.13***	0.15***
			[4.71]		[3.38]	[3.01]	[3.32]
β^{HKM}			0.17***		0.11**	0.11**	0.10*
			[3.19]		[2.33]	[2.33]	[1.85]
Size				−0.47***	−0.47***	−0.36***	−0.33***
				[−12.22]	[−12.20]	[−11.49]	[−9.64]
B/M				0.10	0.09	0.13	0.14
				[0.96]	[0.85]	[1.43]	[1.24]
MOM				0.04	0.04	0.03	−0.16
				[0.19]	[0.24]	[0.17]	[−0.80]
OP				−0.04	−0.04	0.04	−0.06
				[−0.32]	[−0.35]	[0.34]	[−0.57]
I/A				−0.77***	−0.76***	−0.81***	−0.83***
				[−7.40]	[−7.40]	[−7.96]	[−7.68]
IVOL						34.64***	46.65***
						[6.59]	[8.02]
$\beta^{\Delta VXO}$							−8.21
							[−1.59]

Table 5

Abnormal Returns based on Dispersion Beta: Portfolio Approach

This table reports abnormal returns of decile portfolios based on the dispersion beta. Portfolios are value-weighted in Panel A and equal-weighted in Panel B. FF5 is the Fama-French five factor model (Fama and French, 2015), FF5+PS adds the liquidity factor (Pastor and Stambaugh, 2003) to FF5, FF5+MOM adds the momentum factor (Jegadeesh and Titman, 1993) to FF5, FF5+AEM adds the intermediary leverage factor (Adrian, Etula, and Muir, 2014) to FF5, and FF5+HKM adds the intermediary capital factor (He, Kelly, and Manela, 2017) to FF5. The dispersion beta, defined in Table 1, is estimated from quarterly regressions using 5-year rolling windows. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Abnormal Returns of Value-Weighted Portfolios based on Dispersion Beta

	(1)	(2)	(3)	(4)	(5)	(6)
	FF5	FF5 + PS	FF5 + MOM	FF5 + IVOL	FF5 + AEM	FF5 + HKM
H−L	−0.58%***	−0.62%***	−0.62%***	−0.57%***	−0.58%***	−0.57%***
	[−3.20]	[−3.48]	[−3.37]	[−3.15]	[−3.17]	[−3.13]
Low	0.51%***	0.52%***	0.56%***	0.49%***	0.52%***	0.52%***
	[4.09]	[4.31]	[4.39]	[4.03]	[4.17]	[4.10]
2	0.18%	0.17%	0.26%**	0.17%	0.17%	0.16%
	[1.35]	[1.32]	[2.00]	[1.25]	[1.23]	[1.21]
3	0.06%	0.05%	0.10%	0.06%	0.05%	0.06%
	[0.60]	[0.44]	[0.86]	[0.56]	[0.43]	[0.52]
4	0.07%	0.07%	0.09%	0.07%	0.07%	0.06%
	[0.77]	[0.86]	[1.00]	[0.82]	[0.83]	[0.69]
5	0.17%**	0.17%**	0.16%**	0.17%**	0.18%**	0.18%**
	[2.07]	[2.07]	[2.02]	[2.00]	[2.12]	[2.19]
6	0.11%	0.10%	0.10%	0.11%	0.10%	0.11%
	[1.45]	[1.33]	[1.31]	[1.48]	[1.29]	[1.43]
7	0.00%	−0.01%	−0.02%	0.00%	0.00%	0.01%
	[0.07]	[−0.11]	[−0.22]	[0.04]	[0.02]	[0.16]
8	−0.10%	−0.10%	−0.11%	−0.09%	−0.10%	−0.10%
	[−1.19]	[−1.14]	[−1.36]	[−1.11]	[−1.13]	[−1.15]
9	−0.08%	−0.09%	−0.11%	−0.08%	−0.08%	−0.08%
	[−0.79]	[−0.90]	[−1.09]	[−0.75]	[−0.82]	[−0.83]
High	−0.07%	−0.10%	−0.06%	−0.08%	−0.06%	−0.05%
	[−0.52]	[−0.74]	[−0.45]	[−0.60]	[−0.44]	[−0.41]

Panel B: Abnormal Returns of Equal-Weighted Portfolios based on Dispersion Beta

	(1) FF5	(2) FF5 + PS	(3) FF5 + MOM	(4) FF5 + IVOL	(5) FF5 + AEM	(6) FF5 + HKM
H−L	−0.62%***	−0.63%***	−0.68%***	−0.61%***	−0.60%***	−0.61%***
	[−4.62]	[−4.71]	[−5.03]	[−4.56]	[−4.42]	[−4.60]
Low	1.46%***	1.46%***	1.56%***	1.44%***	1.44%***	1.46%***
	[11.36]	[11.83]	[11.98]	[11.56]	[11.06]	[11.23]
2	0.85%***	0.84%***	0.94%***	0.84%***	0.84%***	0.84%***
	[9.71]	[9.73]	[10.88]	[9.75]	[9.59]	[9.61]
3	0.64%***	0.62%***	0.71%***	0.63%***	0.63%***	0.64%***
	[8.92]	[9.06]	[10.59]	[9.01]	[8.81]	[8.80]
4	0.46%***	0.44%***	0.53%***	0.46%***	0.45%***	0.46%***
	[6.90]	[6.83]	[8.88]	[7.01]	[6.82]	[6.70]
5	0.65%***	0.62%***	0.70%***	0.65%***	0.64%***	0.64%***
	[8.24]	[8.22]	[9.38]	[8.32]	[8.32]	[8.15]
6	0.43%***	0.41%***	0.47%***	0.44%***	0.42%***	0.43%***
	[7.25]	[7.03]	[7.86]	[7.25]	[7.26]	[7.17]
7	0.53%***	0.52%***	0.57%***	0.53%***	0.52%***	0.52%***
	[10.26]	[9.80]	[11.14]	[10.39]	[10.22]	[10.11]
8	0.44%***	0.43%***	0.46%***	0.44%***	0.43%***	0.44%***
	[6.52]	[6.12]	[6.65]	[6.55]	[6.39]	[6.56]
9	0.45%***	0.44%***	0.50%***	0.45%***	0.45%***	0.46%***
	[5.87]	[5.65]	[6.54]	[5.90]	[5.91]	[5.93]
High	0.84%***	0.83%***	0.89%***	0.83%***	0.84%***	0.85%***
	[9.68]	[9.79]	[10.96]	[9.79]	[9.70]	[10.24]

Table 6

Trading Volume

This table reports the results of OLS regressions for trading volume of 13F institutional investment managers who belong to the largest 30 intermediaries in the U.S. based on market capitalization. Panels A and B show the results using subsamples of managers who belong to high- and low-capital intermediaries, ones above and below the 50^{th} percentile of intermediary capital. Dependent variables are trading volume of managers from stock trades (i.e., purchases and sales) in quarter t, measured in billion dollars. For each stock, trading volume is computed as the number of shares traded during the quarter t times the price at the end of quarter t. The trading volume for All Stocks is defined as the sum of trading volumes of all stocks traded during the quarter. The trading volume for Stocks ($\Delta IO^L < 0$) is the sum of trading volumes of stocks traded in which low-capital intermediaries reduce their holdings during the quarter. Similarly, the trading volume for Stocks ($\Delta IO^H > 0$) is the sum of trading volumes of stocks traded in which high-capital intermediaries raise their holdings during the quarter. $DISP^{Capr}$ is the dispersion of intermediary capital, defined in Table 1. Intermediary size is measured as the log of the intermediary's market capitalization. Portfolio size is the log of the total portfolio size of the manager. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by 13F manager. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading Volume for Managers of High-Capital Intermediary

	Stock Purchases		*Stock Sales*
	(1)	(2)	(3)
	All Stocks	Stocks ($\Delta IO^L < 0$)	All Stocks
$DISP^{Capr}$	-0.255	1.666**	2.715
	[-0.37]	[2.53]	[0.89]
Intermediary Size	0.044	-0.376	1.088
	[0.08]	[-0.67]	[1.27]
Portfolio Size	1.251***	0.659***	0.373
	[2.82]	[2.73]	[0.90]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	2,072	2,057	2,072
adj. R^2	0.298	0.230	0.239

Panel B: Trading Volume for Managers of Low-Capital Intermediary

	Stock Purchases	*Stock Sales*	
	(1)	(2)	(3)
	All Stocks	All Stocks	Stocks ($\Delta IO^H > 0$)
$DISP^{Capr}$	-6.470**	9.645*	8.310**
	[-2.58]	[1.95]	[2.16]
Intermediary Size	-0.280	2.114**	1.399***
	[-0.19]	[2.59]	[2.75]
Portfolio Size	3.755***	0.271	0.048
	[2.71]	[0.30]	[0.09]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	1,575	1,575	1,574
adj. R^2	0.440	0.338	0.207

Table 7

Trading Gains

This table reports the results of OLS regressions for trading gains of 13F institutional investment managers who belong to the largest 30 intermediaries in the U.S. Panel A shows the results using the whole sample. Panels B and C show the results using subsamples of managers who belong to high- and low-capital intermediaries. Dependent variables are abnormal trading gains for stock purchases (sales) by managers in quarter $t+1$ from stocks purchased (sold) in quarter t, estimated using the Fama-French five factor model (Fama and French, 2015). The sum of trading gains from stock purchases and sales is total grading gains. $\mathbb{1}$(Intermediary Capital = Low) is one if the manager belongs to a low-capital intermediary and zero otherwise. High- and low-capital intermediaries are the ones above and below the 50^{th} percentile of intermediary capital. $DISP^{Capr}$ is the dispersion of intermediary capital, defined in Table 1. Intermediary size is measured as the log of the intermediary's market capitalization. Portfolio size is the log of the total portfolio size of the manager. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by 13F manager. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading Gains by Intermediary Capital

	(1) Total (%)	(2) Buy (%)	(3) Sell (%)
$\mathbb{1}$(Intermediary Capital = Low) × $DISP^{Capr}$	-0.401**	-0.025	-0.375***
	[-2.14]	[-0.21]	[-2.92]
$\mathbb{1}$(Intermediary Capital = Low)	0.408	-0.002	0.411**
	[1.28]	[-0.01]	[2.27]
$DISP^{Capr}$	0.177	0.503**	-0.326*
	[0.68]	[2.43]	[-1.92]
Intermediary Size	0.197	0.063	0.135
	[0.85]	[0.45]	[0.93]
Portfolio Size	0.278*	-0.020	0.299
	[1.88]	[-0.24]	[1.40]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	3,660	3,660	3,660
adj. R^2	0.009	0.005	0.029

Panel B: Trading Gains for Managers of High-Capital Intermediary

	(1) Total (%)	(2) Buy (%)	(3) Sell (%)
$DISP^{Capr}$	0.245	0.600**	-0.355
	[0.77]	[2.14]	[-1.64]
Intermediary Size	0.732	0.266	0.467
	[1.04]	[0.64]	[1.26]
Portfolio Size	0.289	-0.049	0.338
	[1.37]	[-0.33]	[1.02]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	2,072	2,072	2,072
adj. R^2	0.006	-0.009	0.014

Panel C: Trading Gains for Managers of Low-Capital Intermediary

	(1) Total (%)	(2) Buy (%)	(3) Sell (%)
$DISP^{Capr}$	-0.367	0.357*	-0.724***
	[-1.39]	[1.90]	[-4.05]
Intermediary Size	-0.180	-0.105	-0.074
	[-0.78]	[-0.58]	[-0.52]
Portfolio Size	0.283**	0.055	0.228**
	[2.38]	[0.49]	[2.38]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	1,575	1,575	1,575
adj. R^2	0.046	0.073	0.052

Table 8

Trading Activity of Intermediaries and Risk Characteristics of Stocks

This table reports the results of OLS regressions for the trading activity of intermediaries. Panel A presents the trading activities of high-capital intermediaries, and Panel B presents those of low-capital intermediaries. High- and low-capital intermediaries have capital ratios above and below the 50^{th} percentile. Dependent variables are trading volume, defined as the dollar-value of net purchases in a stock during a quarter scaled by the manager's portfolio size. $\mathbb{1}(\beta^{DISP} = \text{High})$ is one if stocks belong to the highest three deciles in the dispersion beta and zero otherwise. $\mathbb{1}(\beta^{DISP} = \text{Med})$ is one if stocks belong to the middle four deciles in the dispersion beta and zero otherwise. $\mathbb{1}(\beta^{DISP} = \text{Low})$ is one if stocks belong to the lowest three deciles in the dispersion beta and zero otherwise. $DISP^{Capr}$ is the dispersion of intermediary capital, defined in Table 1. Intermediary size is the log of the intermediary's market capitalization. β^{MKT} is the market beta, estimated from monthly regressions using 5-year rolling windows. Market Cap is the log of the stock's market capitalization. B/M is the book-to-market ratio, book equity over market capitalization. MOM is momentum, the cumulative return over the previous one year, skipping the most recent month. ROE is income before extraordinary items over lagged book equity. I/A is asset growth, the percentage change in total assets. Return Volatility is the quarterly standard deviation of daily stock returns. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by 13F manager and stock. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading Volume of High-Capital Intermediary

	(1) Volume	(2) Volume	(3) Volume	(4) Volume
$\mathbb{1}(\beta^{DISP} = \text{Low}) \times DISP^{Capr}$	6.787***			6.986***
	[2.72]			[2.74]
$\mathbb{1}(\beta^{DISP} = \text{Med}) \times DISP^{Capr}$		0.498		0.491
		[0.32]		[0.52]
$\mathbb{1}(\beta^{DISP} = \text{High}) \times DISP^{Capr}$			-1.310	0.707
			[-1.00]	[0.47]
$\mathbb{1}(\beta^{DISP} = \text{Low})$	-8.491***			-8.393*
	[-4.46]			[-1.80]
$\mathbb{1}(\beta^{DISP} = \text{Med})$		-3.547***		-3.106
		[-4.28]		[-1.08]
$\mathbb{1}(\beta^{DISP} = \text{High})$			4.315***	0.444
			[6.44]	[0.16]
Intermediary Size	-7.176	-7.181	-7.180	-7.174
	[-0.94]	[-0.94]	[-0.94]	[-0.94]
β^{MKT}	2.394	2.351	2.454	2.345
	[1.45]	[1.38]	[1.47]	[1.41]
Market Cap	0.700	0.621	0.555	0.672
	[0.21]	[0.19]	[0.17]	[0.21]
B/M	-2.357	-2.341	-2.476	-2.250
	[-1.29]	[-1.33]	[-1.38]	[-1.27]
MOM	0.547	0.479	0.546	0.547
	[0.30]	[0.26]	[0.30]	[0.30]
ROE	9.069***	8.822***	8.829***	9.042***
	[2.69]	[2.66]	[2.67]	[2.71]
I/A	11.321***	11.343***	11.438***	11.272***
	[3.84]	[3.84]	[3.85]	[3.84]
Return Volatility	5.216*	4.919*	4.989*	5.111*
	[1.94]	[1.85]	[1.89]	[1.90]
Manager FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes	Yes
N	1,687,770	1,687,770	1,687,770	1,687,770
adj. R^2	0.058	0.058	0.058	0.058

Panel B: Trading Volume of Low-Capital Intermediary

	(1) Volume	(2) Volume	(3) Volume	(4) Volume
$\mathbb{1}(\beta^{DISP} = \text{Low}) \times DISP^{Capr}$	1.646			1.912
	[0.73]			[1.09]
$\mathbb{1}(\beta^{DISP} = \text{Med}) \times DISP^{Capr}$		-4.813**		-4.907***
		[-2.32]		[-5.07]
$\mathbb{1}(\beta^{DISP} = \text{High}) \times DISP^{Capr}$			1.597	0.145
			[0.58]	[0.06]
$\mathbb{1}(\beta^{DISP} = \text{Low})$	0.831			-1.071
	[0.60]			[-0.66]
$\mathbb{1}(\beta^{DISP} = \text{Med})$		6.566**		4.582*
		[2.49]		[1.72]
$\mathbb{1}(\beta^{DISP} = \text{High})$			-6.601	-5.099
			[-1.33]	[-0.90]
Intermediary Size	24.372*	24.363*	24.387*	24.361*
	[1.96]	[1.96]	[1.96]	[1.96]
β^{MKT}	-0.002	0.126	-0.009	-0.042
	[-0.00]	[0.07]	[-0.00]	[-0.02]
Market Cap	-4.321	-4.491*	-4.307*	-4.271
	[-1.66]	[-1.71]	[-1.67]	[-1.66]
B/M	-2.002	-2.219*	-2.002	-2.100*
	[-1.58]	[-1.74]	[-1.64]	[-1.71]
MOM	3.452***	3.502***	3.396***	3.414***
	[2.67]	[2.67]	[2.66]	[2.69]
ROE	5.196***	5.138**	5.150**	5.303***
	[2.67]	[2.60]	[2.63]	[2.73]
I/A	10.939***	10.975***	10.815***	10.884***
	[3.95]	[3.98]	[3.88]	[3.89]
Return Volatility	1.722	1.716	1.869	1.653
	[0.41]	[0.41]	[0.43]	[0.38]
Manager FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes	Yes
N	1,927,980	1,927,980	1,927,980	1,927,980
adj. R^2	0.114	0.114	0.114	0.114

Table 9

Fama-MacBeth Regressions: Controlling for Industry Effect

This table reports the estimation results for the Fama-MacBeth regressions controlling for the industry effect. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 1, is estimated from quarterly regressions using 5-year rolling windows. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 4. To control unobserved heterogeneity across industry, I also include industry fixed effect based on the Fama-French 10-industry classification. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.75***	−0.73***	−0.49***	−0.44***	−0.35***	−0.34***	−0.38***
	[−5.13]	[−5.21]	[−3.92]	[−3.87]	[−3.12]	[−3.16]	[−3.01]
β^{MKT}		0.19	0.19	0.26**	0.28**	0.13	0.18
		[1.25]	[1.28]	[2.05]	[2.10]	[1.13]	[1.36]
β^{AEM}			0.32***		0.15***	0.13***	0.14***
			[5.19]		[3.67]	[3.29]	[3.31]
β^{HKM}			0.13***		0.08**	0.08*	0.08*
			[3.03]		[2.05]	[1.94]	[1.74]
Size				−0.46***	−0.45***	−0.36***	−0.33***
				[−12.49]	[−12.47]	[−11.67]	[−9.90]
B/M				0.22**	0.22**	0.24***	0.24**
				[2.58]	[2.50]	[3.03]	[2.48]
MOM				−0.10	−0.10	−0.10	−0.26
				[−0.57]	[−0.56]	[−0.60]	[−1.35]
OP				0.08	0.07	0.14	0.03
				[0.64]	[0.63]	[1.23]	[0.30]
I/A				−0.85***	−0.85***	−0.88***	−0.87***
				[−8.57]	[−8.60]	[−9.07]	[−8.39]
IVOL						32.25***	44.03***
						[6.52]	[8.16]
$\beta^{\Delta VXO}$							−7.58
							[−1.55]

Table 10

Alternative Dispersion of Capital Ratios: Balancing Size of High- and Low-Capital Intermediaries

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 1, is estimated from quarterly regressions using 5-year rolling windows. To account for the difference in size (i.e., market capitalization) of high- and low-capital intermediaries, the dispersion of intermediary capital is defined differently so that the total market capitalizations of high- and low-capital intermediaries are similar: the difference between the 75^{th} percentile and the 10^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.51***	−0.49***	−0.28**	−0.30***	−0.19**	−0.20**	−0.21**
	[−3.54]	[−3.71]	[−2.38]	[−3.06]	[−2.14]	[−2.30]	[−2.20]
β^{MKT}		0.32*	0.33*	0.28*	0.31**	0.14	0.20
		[1.74]	[1.82]	[1.86]	[2.04]	[1.03]	[1.32]
β^{AEM}			0.35***		0.16***	0.13***	0.16***
			[4.90]		[3.42]	[3.09]	[3.58]
β^{HKM}			0.14***		0.10**	0.11**	0.10*
			[2.67]		[2.18]	[2.26]	[1.79]
Size				−0.47***	−0.47***	−0.36***	−0.33***
				[−12.19]	[−12.19]	[−11.48]	[−9.64]
B/M				0.11	0.10	0.14	0.15
				[1.06]	[0.94]	[1.51]	[1.32]
MOM				0.04	0.05	0.03	−0.16
				[0.21]	[0.25]	[0.17]	[−0.78]
OP				−0.05	−0.04	0.04	−0.06
				[−0.35]	[−0.34]	[0.35]	[−0.56]
I/A				−0.77***	−0.76***	−0.82***	−0.84***
				[−7.42]	[−7.42]	[−7.96]	[−7.66]
IVOL						34.63***	46.63***
						[6.58]	[8.01]
$\beta^{\Delta VXO}$							−8.08
							[−1.57]

Table 11

Alternative Dispersion of Capital Ratios: Using Largest 40 or 50 Intermediaries

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 1, is estimated from quarterly regressions using 5-year rolling windows. However, the dispersion of intermediary capital is defined using the largest 40 or 50 intermediaries. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 40 or 50 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Top 40 Intermediaries			*Top 50 Intermediaries*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.47***	−0.67***	−0.26*	−0.41***	−0.26*	−0.17
	[−2.72]	[−4.07]	[−1.91]	[−2.89]	[−1.96]	[−1.40]
β^{MKT}	0.30*	0.32*	0.15	0.34*	0.32*	0.13
	[1.68]	[1.82]	[1.17]	[1.85]	[1.79]	[1.02]
β^{AEM}		0.29***	0.11**		0.35***	0.15***
		[3.93]	[2.15]		[5.15]	[3.60]
β^{HKM}		0.17***	0.12**		0.20***	0.13***
		[3.19]	[2.52]		[3.73]	[2.77]
Size			−0.36***			−0.36***
			[−11.74]			[−11.61]
B/M			0.14			0.14
			[1.46]			[1.52]
MOM			0.04			0.02
			[0.25]			[0.13]
OP			0.03			0.04
			[0.28]			[0.36]
I/A			−0.83***			−0.82***
			[−8.08]			[−7.93]
IVOL			34.26***			34.75***
			[6.50]			[6.61]

Table 12

Alternative Dispersion of Capital Ratios: Using Book Capital Ratio

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 1, is estimated from quarterly regressions using 5-year rolling windows. However, the dispersion of intermediary capital is defined using the book capital ratio (instead of the quasi-market capital ratio). I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 40 or 50 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.40**	−0.36**	−0.40**	−0.08	−0.15	−0.14	0.01
	[−2.34]	[−2.25]	[−2.45]	[−0.67]	[−1.07]	[−1.06]	[0.04]
β^{MKT}		0.31*	0.32*	0.30**	0.32**	0.14	0.21
		[1.72]	[1.76]	[1.99]	[2.06]	[1.08]	[1.37]
β^{AEM}			0.27***		0.10**	0.08*	0.14***
			[3.56]		[2.09]	[1.74]	[2.73]
β^{HKM}			0.21***		0.13***	0.13***	0.12**
			[4.17]		[2.78]	[2.79]	[2.31]
Size				−0.47***	−0.47***	−0.36***	−0.33***
				[−12.33]	[−12.19]	[−11.46]	[−9.71]
B/M				0.11	0.09	0.14	0.14
				[1.02]	[0.89]	[1.45]	[1.24]
MOM				0.03	0.03	0.01	−0.16
				[0.17]	[0.14]	[0.05]	[−0.81]
OP				−0.04	−0.05	0.04	−0.06
				[−0.34]	[−0.37]	[0.30]	[−0.53]
I/A				−0.77***	−0.76***	−0.82***	−0.83***
				[−7.38]	[−7.43]	[−7.99]	[−7.63]
IVOL						34.71***	46.91***
						[6.58]	[8.05]
$\beta^{\Delta VXO}$							−7.97
							[−1.54]

Table 13
Subsample Tests

This table reports the estimation results for the Fama-MacBeth regressions in subsample periods. In columns (1) - (3) of Panel A, the sample period covers January 1978 to December 1999. In columns (4) - (6) of Panel A, the sample period covers January 2000 to December 2016. In Panel B, the financial crisis (July 2007 to December 2009) and NBER recessions are excluded from the sample period in columns (1) - (3) and columns (4) - (6), respectively. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 1, is estimated from quarterly regressions using 5-year rolling windows. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). Standard errors are adjusted using the Newey-West method. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Subsample Periods Before and After 2000

Sample Period	*1978 - 1999*			*2000 - 2016*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.60***	−0.53**	−0.33**	−1.01***	−0.45**	−0.33*
	[−2.74]	[−2.36]	[−2.00]	[−3.97]	[−2.36]	[−1.87]
β^{MKT}	0.19	0.15	0.13	0.42	0.51*	0.12
	[0.85]	[0.66]	[0.77]	[1.48]	[1.84]	[0.63]
β^{AEM}		0.23***	0.06		0.44***	0.21***
		[2.95]	[1.09]		[3.76]	[3.38]
β^{HKM}		0.08	−0.00		0.28***	0.25***
		[1.36]	[−0.03]		[3.10]	[3.28]
Size			−0.33***			−0.40***
			[−7.81]			[−8.82]
B/M			0.17			0.09
			[1.62]			[0.54]
MOM			0.65***			−0.76**
			[4.25]			[−2.38]
OP			0.11			−0.06
			[0.62]			[−0.47]
I/A			−0.89***			−0.71***
			[−6.43]			[−4.85]
IVOL			23.69***			48.65***
			[3.94]			[5.97]

Panel B: Subsample Periods Excluding Bad Times

Sample Period	*Excluding Financial Crisis*			*Excluding NBER Recessions*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.75***	−0.53***	−0.38***	−0.75***	−0.52***	−0.36***
	[−4.50]	[−3.42]	[−3.09]	[−4.47]	[−3.33]	[−2.83]
β^{MKT}	0.19	0.21	0.10	0.23	0.25	0.10
	[1.09]	[1.23]	[0.78]	[1.41]	[1.51]	[0.82]
β^{AEM}		0.27***	0.12***		0.29***	0.13***
		[4.67]	[2.74]		[4.52]	[2.77]
β^{HKM}		0.16***	0.09*		0.16***	0.10*
		[2.99]	[1.88]		[2.77]	[1.86]
Size			−0.37***			−0.35***
			[−11.11]			[−10.24]
B/M			0.16*			0.17*
			[1.82]			[1.76]
MOM			0.22*			0.13
			[1.71]			[0.91]
OP			0.07			−0.00
			[0.59]			[−0.01]
I/A			−0.83***			−0.85***
			[−7.79]			[−7.67]
IVOL			34.19***			36.42***
			[6.38]			[6.54]

Table 14

Calibration

This table reports the numerical example of the model. Panel A presents parameters used in the calibration. Panel B shows outcomes of the calibration: risk premium, $E[r^a_{t+1} - r^f_{t+1}]$, risk aversion of specialists, Γ^I_1, intermediary leverage, α^I_1, and intermediary capital, κ^I_1 for $I \in \{H, L\}$. The first column indicates the baseline outcome based on the parameters in Panel A. In the remaining columns in Panel B, I also present how the baseline outcome varies by changing a parameter indicated in the first row while keeping other parameters constant.

Panel A: Parameter Choices

Parameter	Description	Value
μ	Unconditional Mean of Return on Risky Asset	10%
σ	Unconditional Volatility of Return on Risky Asset	14%
r^f	Return on Risk-Free Asset	4%
e^I	Initial Endowment of Specialists	100
e^{hh}	Initial Endowment of Household	100
ρ	Time Preference	0.05
γ	Curvature Parameter of Specialists' Utility Function	2
η	Habit Persistence (Common)	0.95
ϕ^H	Habit Persistence (type = H)	0.9
ϕ_L	Habit Persistence (type = L)	0.1
A	Risk Aversion of Household	3
g	Consumption Growth	0.02
σ_c	Consumption Volatility	0.02

Panel B: Simulation Outcomes

Outcome	Baseline	$(\phi_H, \phi_L) = (0.6, 0.3)$	$\gamma = 1$	$A = 5$	$\eta = 0.65$
Risk Premium	8.44%	11.79%	4.17%	8.82%	11.79%
Risk Premium due to *Capital Level*	2.47%	4.36%	1.49%	2.58%	4.26%
Risk Premium due to *Capital Dispersion*	5.97%	7.44%	2.68%	6.24%	7.53%
Risk Aversion (type = H)	12.50	4.54	6.25	12.5	4.69
Risk Aversion (type = L)	2.21	2.78	1.10	2.21	2.14
Leverage (type = H)	0.37	1.01	0.74	0.37	0.98
Leverage (type = L)	2.08	1.65	4.16	2.08	2.15
Intermediary Capital (type = H)	105.0	105.0	88.7	88.3	95.9
Intermediary Capital (type = L)	52.6	48.7	25.7	36.0	34.9