Intermediation Frictions in Equity Markets

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Abstract

Stocks with similar characteristics but different levels of ownership by financial institutions have returns and risk premia that comove very differently with shocks to the risk bearing capacity of financial intermediaries. After accounting for observable stock characteristics, excess returns on more intermediated stocks have higher betas on contemporaneous shocks to intermediary willingness to take risk and are more predictable by state variables that proxy for intermediary health. The empirical evidence suggests that asset pricing models featuring financial intermediaries as marginal investors and frictions that induce changes in intermediary risk bearing capacity are useful in explaining price movements even in asset classes with comparatively low barriers to household participation.

1 Introduction

Empirical evidence has recently accumulated in favor of asset pricing models with frictions and that feature sophisticated financial intermediaries as the marginal investors. This has been particularly so in complex asset classes. At the same time, the relevance of these sorts of theories for explaining stock price movements has been questioned, even among proponents of intermediary asset pricing. Due to the comparative ease of household stock market participation, there is cause for such skepticism towards theories of frictional intermediation in equity markets. Despite the success of intermediary-based empirical asset pricing models, such as Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017), in explaining cross-sections of returns on stocks and other asset classes, such tests cannot rule out that a household-based pricing kernel also holds in equity markets.

However, if households and institutional investors have differential preferences for direct holding of certain stocks for any reason unrelated to the true distributions of cashflows, whether for heterogeneous beliefs or different trading costs, dispersion in intermediation independent of fundamentals can arise naturally in the cross section, even when households are not prevented from trading directly. This dispersion leads to similar patterns in asset covariances with shocks to intermediaries as in models where intermediaries face constraints and households are impeded from trading directly. The basic prediction is that for two otherwise similar assets, the more intermediated asset exhibits larger price response and risk premia variation due to shifts in intermediary risk bearing capacity.

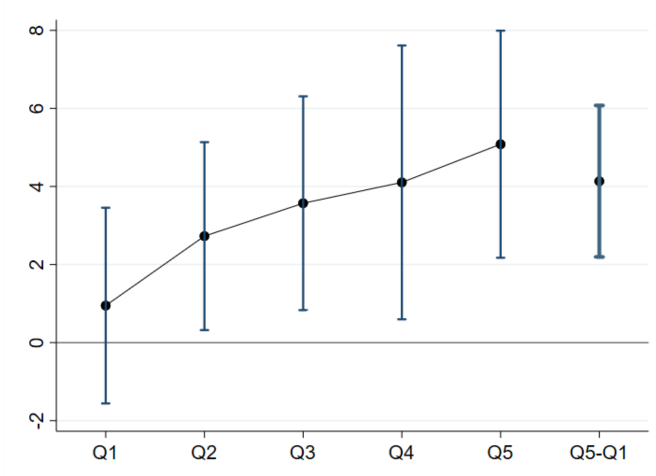
I find evidence strongly in support of this implication within the equity asset class. After accounting for firm characteristics, excess returns on stocks that are held more by some of the largest and most active institutional investors in equity markets (mutual funds, hedge funds, and other investment advisors) covary more with theoretically-motivated empirical proxies for shocks to intermediary risk tolerance. My main empirical proxy combines the two primary empirical measures of shocks to an intermediary pricing kernel proposed in the literature. Adrian, Etula, and Muir (2014) propose shocks to broker-dealer book leverage, while He, Kelly, and Manela (2017) use shocks to the market equity capital ratio of Federal Reserve primary dealer bank holding companies. I simply standardize both of these measures and take the average of the two, similarly to the approach in Haddad and Muir (2018), who argue that doing so provides a good proxy for average financial sector willingness to take risk. I also include tests with these measures separately, which provide evidence consistent with my main proxy that combines the two. I further show that another credible proxy for shocks to financial sector risk bearing capacity–the excess return on the financial sector–displays the same empirical pattern of increased exposure to shocks to intermediary risk bearing capacity along the dimension of increased intermediation.

Figure 1 illustrates some of my findings for betas on contemporaneous shocks to intermediary capital. Stocks sorted on a measure of intermediation that holds stock fundamentals constant have monotonically increasing betas on intermediary capital shocks; a portfolio formed on stocks from the top quintile of my intermediation measure has a beta of about 5.1 on intermediary capital shocks, while the beta on the lowest quintile is about 0.9. Moreover, intermediary shocks significantly explain the spread in returns between the top and bottom portfolios, with a t-stat of 4.21.

Predictive tests using state variables proposed in the literature to capture intermediary willingness to take risk also exhibit a pattern in line with the mechanisms illustrated in intermediary asset pricing models. Namely, state variables that proxy for higher (lower) willingness to take risk predict returns more negatively (positively) for similar stocks that are more intermediated. Following He, Kelly, and Manela (2017), I use the squared market leverage ratio of Federal Reserve primary dealer bank holding companies and the book leverage ratio of broker dealers obtained from the Flow of Funds accounts in predictability tests, taking the average of the standardized versions of these two state variables as my main proxy for intermediary risk appetite at the current date.[1] I also show that these

[1]As He, Kelly, and Manela (2017) point out, these two state variables predict stock market returns with opposite sign. Hence, when I take the average I take the negative of the broker-dealer leverage ratio so that the composite measure predicts returns with a positive sign.

Figure 1: **Coefficients on Intermediary Shocks Over Portfolios Formed on Intermediation Quintile**



This figure shows the coefficient estimates on the average of the standardized Federal Reserve primary dealer equity capital ratio shocks from He, Kelly, and Manela (2017) and the broker-dealer book leverage growth shocks from Adrian, Etula, and Muir (2014) for five portfolios formed on the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail), as well as the coefficient on the intermediary shocks for the top minus bottom quintile spread. The sample is quarterly and comprises 1980q2 to 2017q3. The confidence bands represent 95% confidence intervals computed from Newey-West standard errors.

measures perform well when included separately, and another proxy motivated by theory, financial sector stock market wealth share, predicts returns more negatively for the more intermediated stocks as implied by the theory.

The predictability tests suggest that discount rates on more intermediated stocks respond more to shocks to intermediary risk bearing capacity, a fundamental feature in models of intermediary asset pricing. Such implications are discussed in more detail in section 2, where I present a simple model in which intermediary risk tolerance can shift as a result of shocks to some underlying state variables. Shocks to these state variables implicitly represent shocks to the capitalization of intermediaries that cause financial constraints on intermediaries to be more binding, which basic mechanism is inspired by numerous papers from the intermediary asset pricing literature.

I include an additional test confirming a feature in the cross-section of return predictability which is consistent with theory, though it is not explicitly laid out in my simple static model. I find that the predictive coefficients for the return spread between high- and low-intermediation portfolios are positive but declining with the time horizon of the monthly returns being predicted, and the R^2 is also decreasing with the time horizon. This suggests temporary distortions in relative discount rates between more and less intermediated stocks that are induced by shocks to intermediaries, which distortions revert over time as intermediary capital recovers.[2]

The proxies for intermediary risk tolerance shocks proposed by He, Kelly, and Manela (2017) and Adrian, Etula, and Muir (2014) focus on a set of levered institutions–namely dealer banks and other broker-dealers–that have been argued in the literature to occupy a place of central importance in financial markets and as marginal investors in pricing numerous asset classes; however, they are not the same set of institutions whose stock holdings I measure (though there is some overlap). The empirical evidence I present in section 4 implies that these shocks also affect the risk bearing capacity of the mutual funds, hedge funds, and other investment advisors whose holdings are included in my analysis. Therefore in section 5 I suggest reasons that the risk bearing capacity of these classes of financial institutions are interlinked.

In my primary tests I construct a measure of stock-level intermediation that holds firm size, pre-ranking CAPM beta, book-to-market, firm profitability, and investment constant, while retaining wide variation in intermediation.[3] I do this by running cross-sectional regressions of stock percentage intermediated on stock characteristics and sorting on the residuals. In the appendix I demonstrate that this cross-sectional regression specification isolates a component of intermediary holdings that is unrelated to fundamentals and along which the stock price response is monotonically increasing with shocks to intermediary risk bearing

[2] This mechanism is outlined theoretically in Gromb and Vayanos (2018), for example.

[3] I construct the accounting-based characteristics following Koijen and Yogo (2019), who in turn follow the steps outlined in Fama and French (2015).

capacity; in particular, this specification arises in a setting related to the characteristics-demand setup of Koijen and Yogo (2019) when households and financial institutions believe that expected asset cashflows and covariances are linear in characteristics. I also show that my findings don't depend crucially on the set of characteristics considered, so long as stock size is accounted for. In robustness checks I show that constructing a measure of intermediation that is uncorrelated with dozens of additional stock characteristics leaves results unchanged. These findings similarly hold after just controlling for stock size in the cross-sectional regressions.

Analysis at the individual stock-level via panel regressions corroborate portfolio-level evidence–more intermediated individual stocks have increasing betas on contemporaneous capital shocks and their returns are more predictable by the current capitalization of financial intermediaries. Consider two stocks with the exact same characteristics, with one being fully intermediated and the other owned entirely by households. My estimates indicate that a one-standard deviation negative shock to intermediary risk bearing capacity decreases the return on the fully intermediated stock by about 8-10% on an annualized basis relative to the non-intermediated stock. Meanwhile, predictive regressions imply that a one-standard deviation decrease in the time t intermediary risk tolerance increases the expected return on the intermediated stock by about 11 to 12% on an annualized basis relative to the stock owned entirely by households.

Theoretical support for my empirical strategy is demonstrated in a simple economic setting introduced in section 2. The model shows that if households are relatively more willing to hold one asset for any reason unrelated to the true distribution of cash flows, assets that are less preferred by households become more intermediated and have risk premia that respond more to shocks to the intermediaries' risk tolerance. In my setting this increased intermediary willingness to hold certain assets comes because households have either heterogeneous expectations errors or view direct investing in certain assets as relatively more or less costly. The empirical implication is that relatively more intermediated assets that are similar on fundamentals should have prices that move more with contemporaneous intermediary shocks and risk premia that are more predictable by state variables representing intermediary risk tolerance.

1.1 Contribution to the Literature

The literature connecting the marginal value of wealth of financial intermediaries to asset price movements has grown rapidly in the aftermath of the financial crisis of 2008-2009, which brought such theories to the forefront. Since then, theories of frictional intermediation have found empirical support in many asset classes.[4] Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) show using classical asset pricing tests that proxies for the marginal utility of a representative intermediary successfully price large cross sections of portfolios spanning multiple asset classes. Such tests imply that intermediaries are marginal investors in many markets.[5] These asset pricing tests do not necessarily mean that intermediation frictions matter for price movements in all markets, because they do not preclude the possibility that households are jointly marginal with sophisticated intermediaries in certain asset classes. They also do not rule out that intermediaries' investment decisions merely directly reflect the preferences of households on whose behalf they make their investment decisions.

Haddad and Muir (2018) address this issue by constructing empirical tests designed to detect whether intermediaries matter for asset price movements or if they merely act as a veil to pass on household preferences. Their estimates imply that intermediation frictions do matter, especially in credit default swap, foreign exchange, commodities, and sovereign bond markets. On the other hand, they argue that equities are the least likely asset class

[4] For example, markets for credit-default swaps (Siriwardane, 2018 and Mitchell and Pulvino, 2012); convertible bonds (Mitchell, Pedersen, and Pulvino, 2007); foreign exchange (Du, Tepper, and Verdelhan, 2018); life insurance (Koijen and Yogo, 2015); treasuries (Haddad and Sraer, 2018, and Anderson and Liu, 2018); and, mortgage-backed securities (Krishnamurthy, 2010 and Gabaix, Krishnamurthy, and Veron, 2007), to name just a few examples.

[5] See also Muir (2017), Chen, Joslin and Ni (2016), Adrian, Moench, and Shin (2014), and Ma (2019) for further empirical evidence on the connection between the health of financial intermediaries and asset prices.

to find price movements due to intermediation frictions (though they cannot rule out their presence). Moreover, their focus is on making comparisons across broad asset class representative portfolios; my focus is on heterogeneity in responses to shocks to intermediaries within the equity asset class.

Other papers in this literature have expressed skepticism towards the relevance of these theories in explaining price movements in equity markets. While He, Kelly, and Manela (2017) find that their proxy for a representative intermediary stochastic discount factor performs reasonably well in describing cross-sections of equity returns, they also argue that equity may be the asset class least fitting to their setting and suggest that intermediaries may act as a veil that merely passes through the preferences of households in equity markets. Similarly in the theoretical literature He and Krishnamurthy (2013) think of their model in the context of complex asset markets such as mortgage backed securities as opposed to equities. A recent intermediary asset pricing paper that does focus on equity markets is Koijen and Yogo (2019), who estimate a characteristics-based demand system for heterogeneous financial intermediaries in equity markets; however, they don't attempt to test how their findings relate to friction-based intermediary asset pricing.[6]

I contribute to this literature by demonstrating that theories of frictional intermediation do appear to matter for asset price movements in equity markets. In particular, my within-asset class findings complement the between-asset class comparisons of Haddad and Muir (2018). This paper also helps address the question posed by Cochrane (2011), which is to explain *why* certain assets covary more with particular risk factors, rather than just examining the cross-sectional asset pricing performance of factor models without any accounting for determinants of the risk exposures. This paper demonstrates that risk factor loadings are in part determined endogenously merely by the agents who own a given asset.

In a related paper, Cho (2019) finds that stocks with higher arbitrage position (determined by abnormally high/low short interest in a stock) explains betas on shocks to the

[6] I draw from the set of stock characteristics that they use to create my primary measure of stock-level intermediation (as detailed in section 4).

Adrian, Etula, and Muir (2014) leverage factor in the post-1993 period when hedge funds became more active in equity markets. I also focus on equity markets, but consider the holdings of a much larger class of financial institutions and for multiple definitions of intermediary shocks; analyze effects both at the portfolio and individual stock level; and, include contemporaneous and predictive tests using shocks to and levels of the state-variables implied by intermediary asset pricing models.

Cho (2019) contextualizes his findings within the Kondor and Vayanos (2019) setting of minimal frictions. By contrast, I prefer the friction-based interpretation, since the empirical measures proposed by Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) are constructed to proxy for mechanisms described in friction-based models–Brunnermeier and Pedersen (2009) and Adrian and Boyarchenko (2012) in the case of Adrian, Etula, and Muir (2014), and He and Krishnamurthy (2013) and Brunnermeier Sannikov (2014) in the case of He, Kelly, and Manela (2017). In Adrian, Etula, and Muir (2014) the underlying friction comes from time-varying margin constraints, while in He, Kelly, and Manela (2017) the friction entails an equity capital constraint imposed by investors in the equity of the intermediary because of moral hazard problems in delegation to professional asset managers. These frictions naturally lead to time-varying intermediary risk-bearing capacity, which is the key mechanism I focus on in my model to derive the predictions that I test in the data.

Besides the primary connection with the theoretical and empirical literature in intermediary asset pricing, this paper also has connections with research areas such as limits to arbitrage[7] and the effects of institutional ownership on asset prices.[8]

In section 3 I describe the data used and sampling criteria. Section 4 describes in detail my empirical strategy and presents my empirical findings. In section 4.1 I explain in more detail the construction of my stock-level intermediation measure and why the intermediary shocks suggested by He, Kelly, and Manela (2017) and Adrian, Etula, and Muir (2014) can be considered proxies for changes in financial risk-bearing capacity. Sections 4.2-4.4 show my

[7]See for example Shleifer and Vishny (1995) and Duffie (2010)

[8]See for example Gompers and Metrick (2001), Nagel (2005) and Basak and Pavlova (2013)

main findings, including portfolio- and stock-level analysis and robustness checks. Section 5 features a discussion on my empirical findings, including an examination of why the shocks to levered intermediaries proposed in the literature may be directly connected to the marginal utility/risk-bearing capacity of the financial institutions (mutual funds, hedge funds, and other large investment advisors) whose asset holdings I include; finally, section 6 provides some brief concluding remarks.

2 An Economic Setting For Empirical Tests

Theories linking asset price movements to intermediary health broadly divide into equity constraint models where financial constraints bind when intermediaries' net worth is low;[9] and, another a class of models where constraints explicitly limit the amount of leverage or risk that intermediaries can take on.[10] To set the stage for my empirical tests I present a simple model that takes the middle ground between these two broad classes of intermediary asset pricing models by allowing risk bearing capacity to vary due to underlying state variables, which could be proxies for net worth shocks or changes in leverage/margin constraints. The intended interpretation is that these shifts in willingness to take on risk come from constraints that exist due to underlying agency frictions in delegation to intermediaries, which is a unifying theme in these models. Though I present my theoretical predictions using a slightly different setting, the intuition and consequent empirical implications in this section draw heavily from the models of He and Krishnamurthy (2018) and Haddad and Muir (2018).

There are two agents, a representative institutional investor/intermediary (labelled "I") and a sophisticated household that can access stock markets directly (labelled "H"). The intermediary invests on behalf of an unmodeled household sector that cannot (or chooses

[9]See Bernanke and Gertler (1989) and Holmstrom and Tirole (1997) for early examples, and more recently Brunnermeier and Sannikov (2014) and He and Krishnamurthy (2013).

[10]Examples from this literature include Brunnermeier and Pedersen (2009), Adrian and Shin (2014), and Garleanu and Pedersen (2011).

not to) invest directly in the stock market. There are N risky assets each in net supply 1 with payoffs that are jointly normally distributed

$$D \sim N(\mu, \Sigma) \tag{1}$$

For simplicity I assume here that Σ is diagonal.[11] Agents have constant absolute risk-aversion utility. Intermediaries have coefficient of constant absolute risk aversion $\gamma_I(\omega)$, which is a function of a state variable (or variables) ω. In the same manner households have coefficient of absolute risk aversion $\gamma_H(\zeta)$, which I allow to be a function of a state variable (or variables) ζ. There is a risk-free asset with exogenously fixed gross rate of return R_f.

I make the following assumption that generates heterogeneity in intermediation independent of asset payoffs:

Key Assumption: Households invest as if $D \sim N(\mu + \lambda, \Sigma)$ for some vector λ.

The interpretation of λ is to reflect potentially heterogeneous expectations errors across stocks by households, or more broadly that households could have preferences for holding certain stocks for reasons unrelated to cashflow distributions (i.e. differences in perceived costliness of holding certain stocks). In more general terms, the presence of λ captures a feature that is present in many intermediary asset pricing models, which is that households' expertise in direct investing is limited in some way relative to intermediaries'.

Both agents maximize the expected utility of period 1 wealth. Given CARA utility, the total wealth invested in risky assets is independent of initial wealth, and the normality of returns yields the familiar mean-variance criterion for portfolio choice for agent j:

$$\theta_j = \frac{1}{\gamma_j}\Sigma^{-1}(\mu_j - R_f P) \tag{2}$$

where γ_j is agent j's absolute risk aversion and μ_j is agent j's beliefs about expected cash-flows.

[11] I relax this assumption in a characteristics-based extension on the model in Appendix A.

The market clearing condition is

$$\mathbf{1} = \theta_I + \theta_H \tag{3}$$

Now denote by $\rho_j \equiv \frac{1}{\gamma_j}$, the risk-tolerance of agent j. Plugging in (2) for $j = I, H$ and solving for P gives

$$P = \frac{\rho_I(\omega)\mu + \rho_H(\zeta)(\mu + \lambda) - \Sigma\mathbf{1}}{(\rho_I(\omega) + \rho_H(\zeta))\, R_f} \tag{4}$$

The percent held by intermediaries can be expressed as

$$\theta_I = \rho_I(\omega)\Sigma^{-1}\left[\frac{-\lambda\rho_H(\zeta) + \Sigma\mathbf{1}}{\rho_I(\omega) + \rho_H(\zeta)}\right] \tag{5}$$

Therefore the percent intermediated is strictly decreasing in λ. Consider a local shock to P by taking the total derivative:

$$\mathrm{d}P = \frac{\rho_I^{'}(\omega)(\Sigma\mathbf{1} - \lambda\rho_H(\zeta))}{R_f(\rho_I(\omega) + \rho_H(\zeta))^2}\mathrm{d}\omega + \frac{\rho_H^{'}(\zeta)(\Sigma\mathbf{1} + \lambda\rho_I(\omega))}{R_f(\rho_I(\omega) + \rho_H(\zeta))^2}\mathrm{d}\zeta \tag{6}$$

$$\equiv \beta_\omega d\omega + \beta_\zeta d\zeta$$

This equation leads to one of the key implications of the model:

Proposition 1 *Suppose $\rho_I^{'}(\omega) > 0$. The component of the total derivative dP due to changes in ω, β_ω, is strictly increasing in θ_I (percent intermediated).*

Proof: Follows immediately from the positivity of $\rho_I^{'}(\omega)$, the fact that θ_I is strictly decreasing in λ, and that the first term on the right-hand side of (6) is strictly decreasing in λ.

Note that (6) resembles a regression of the local change in stock price ("stock return") on shocks to ω and ζ. In other words, proposition 1 implies that the beta on a shock that increases (decreases) the intermediaries' risk tolerance is increasing (decreasing) in the percent intermediated. This is emphasized by He and Krishnamurthy (2018), and is the first theoretical implication that I test in the data. Equation (6) also underscores an issue highlighted by

Haddad and Muir (2018), which is the potentially confounding effect of shocks that change the risk tolerance of households (if $\rho^{'}(\zeta) \neq 0$ and shocks to ω and ζ are correlated). As such, in my empirical implementation I include shocks that could potentially proxy for changes in household-level risk aversion.

Observe also the loading on the shock to household risk tolerance:

$$\frac{\rho_H^{'}(\zeta)(\Sigma\mathbf{1} + \lambda\rho_I(\omega))}{R_f(\rho_I(\omega) + \rho_H(\zeta))^2}\mathrm{d}\zeta \tag{7}$$

If $\rho_H^{'} > 0$, then this is increasing in λ and hence is decreasing in percent intermediated. The rate of decrease depends upon the slope $\rho_H^{'}$. In my empirical tests I find that betas on non-intermediary risk factors are relatively flat in the dimension of increased intermediation, implying that the slope $\rho_H^{'}$ is also relatively flat.

Prices in (4) are increasing in λ. Returning to the example of two similar stocks with $\lambda_1 < \lambda_2$; the price P_2 is higher than P_1, and this difference is decreasing in $\rho(\omega)$. The implications of this fact are summarized in the following proposition:

Proposition 2 *Consider two assets such that $\mu_1 = \mu_2$ and $\sigma_1^2 = \sigma_2^2$ and $\lambda_1 < \lambda_2$. Let $E[R_{p,i}] = \mu_i - R_f P_i$ denote the risk premium on asset i. Then the difference in the risk premium on asset 1 and asset 2 decreases with ω, i.e. $\partial\left(E[R_{p,1} - R_{p,2}]\right)/\partial\omega < 0$.*

Proposition (2) states that for two similar stocks, state variables proxying for higher (lower) intermediary risk tolerance predict returns more negatively (positively) for the stock that is more intermediated. In order to test Proposition (2) empirically, I regress the excess returns of high minus low intermediation stock portfolios on predetermined proxies for intermediary risk bearing capacity. Similarly for Proposition (1), I regress stock returns on portfolios sorted on quintiles of my intermediation measure, as well as the high minus low intermediation portfolio excess returns, on contemporaneous shocks to risk bearing capacity. In section 4.1 I describe in detail the construction of my intermediation measure, which is constructed so as to hold stock fundamentals constant while isolating the effects of increasing intermediation (lower λ). As is discussed briefly in section 4.1 and in more detail in Appendix A, this exact empirical specification arises in a setting closely related to Koijen and Yogo (2019), where I assume that the representative household and intermediary's assessments of fundamental asset means and covariances are linear in characteristics.

Appendix B provides a minor extension on the model that examines the empirical implications for the case when household risk tolerance also responds in the same direction to shocks to the intermediary state variable(s) ω as intermediary risk tolerance. I show that in this case the presence of an increasing price response to intermediary shocks must come through the intermediary risk aversion channel and not through the shocks to household risk aversion, which actually works against finding an effect. I present this as a third proposition:

Proposition 3 *Suppose that household risk tolerance is also a function of the same state variable(s) ω as intermediary risk tolerance and the partial derivative of $\rho_H(\omega, \zeta)$ with respect to ω is positive. Then, holding all else constant, the presence of increasing price responses to ω shocks for more intermediated assets must be driven by shocks to intermediary risk tolerance and not by shocks to household risk tolerance.*

Proof: See Appendix B.

This logic also extends to the setting where $\rho_H(\zeta)$ does not depend directly on ω as in equation (6). If shocks to ζ and ω are positively correlated and $\rho_H' > 0$, the exclusion of shocks to ζ actually work *against* finding an effect, because the coefficient on $d\zeta$ is decreasing in percent intermediated while the coefficient on $d\omega$ is increasing. As Haddad and Muir (2018) point out, it is likely that financial institutions' risk tolerance shocks are positively correlated with those of households, so this seems to be the relevant case empirically.

Observe that the model implies the spread in betas are due to discount rate effects: price appreciation in a more intermediated stock occurs due to positive shocks to intermediaries' willingness to take risk, absent any fundamental information about stock cashflows. Though discount rate and cashflow components of returns cannot be observed perfectly, the combined presence of return predictability using pre-determined state variables and price movements induced by contemporaneous shocks to the same state variables would constitute strong evidence that the effects are driven through the discount rate component of returns. Because of this I include both contemporaneous and predictive tests of the model's implications.

The choice to have absolute risk aversion vary as a function of underlying state variables is obviously critical to the model's predictions and deserves further attention. Since the coefficient of relative risk aversion is related to the coefficient of absolute risk aversion by $w_I \gamma_I = \alpha_I$ (where w_I is the agent's wealth, γ_I is the absolute risk aversion, and α_I the relative risk aversion) allowing γ_I to vary as a function of wealth or wealth share captures effects resembling the wealth effects present in intermediary asset pricing models with constant relative risk aversion of specialists. He and Krishnamurthy (2013) is one such example. In this model wealth shocks lead to changes in risk premia, as the distribution of wealth shifts between agents with different willingness or ability to bear risk. These effects have outsize influence in the constrained region of the model, when equity capital constraints bind and intermediaries require price concessions in order to bear aggregate risk.

The presence of risk aversion is not required for intermediaries to exhibit time-varying risk-bearing capacity so long as there are binding constraints. Brunnermeier and Sannikov (2014) work with risk-neutral agents and find that specialists' wealth share is a critical state variable, generating large spikes in risk premia in the constrained region just as in He and Krishnamurthy (2013). Adrian, Etula, and Muir (2014) point out that in a setting resembling Brunnermeier and Pedersen (2009) with margin constraints, time variation in the margin constraint can lead to non-trivial state pricing where risk-neutral intermediaries value a dollar of wealth relatively more when the Lagrange multiplier on the margin constraint is higher and the value of relaxing the constraint is larger. When margin constraints are tighter, intermediaries invest as if they were more risk averse. Adrian, Etula, and Muir (2014) argue that their leverage measure (which is the reciprocal of margin) proxies for the tightness of leverage constraints and hence risk bearing capacity. In this sense, having risk-tolerance shift due to intermediary shocks is a sort of reduced-form way of capturing the price effects of such mechanisms. Furthermore, allowing households' absolute risk aversion to vary as a function of state variables can capture features related to time-variation in household risk aversion, as would be found in a habit model, for example.

In summary, the crux of the model's predictions are this: if (1) intermediary risk tolerance is time-varying and we have suitable proxies for this time variance; (2) households make expectations errors (or have direct investment costs) that are different across stocks; and, (3) there is variation in households' expectations errors (or direct investment costs) across otherwise similar assets; then we should be able to detect the effects detailed in propositions 1 and 2. The justification behind point (1) comes from the literature on friction-based intermediary asset pricing models. Point (2) can be seen as resulting from limited rationality/information processing capacity of households relative to more sophisticated institutional investors; similar features are present in numerous asset pricing models. I argue point (3) by demonstrating in section 4.1 that I can construct a measure that holds fundamental stock information constant yet still generates a large spread in average intermediation.

3 Data Sources And Sample Construction

Before proceeding to the empirical implementation I first describe the datasets used and sampling procedure followed. Individual monthly firm stock returns are from CRSP. The sample is restricted to ordinary common shares (share codes 10 or 11) and that trade on the NYSE, Amex, or Nasdaq (exchange codes 1, 2, or 3). Institutional holdings data for individual stocks come from the Thomson-Reuters Institutional Holdings Database (S34 file). Due to well-documented errors in the S34 database institutional type classifications, I use the corrected type codes that are provided by Koijen and Yogo (2019) to classify institutions into mutual funds and other investment advisors (which category prominently includes the largest hedge funds).[12] I download the quarterly holdings data from 1980q1 to 2017q2.

[12] For a more detailed description of this data see Gompers and Metrick (2001), or more recently Koijen and Yogo (2019)

My primary set of stock characteristics are originally derived from Compustat, but are taken directly from Koijen and Yogo (2019), whose paper on characteristics-based demand of financial institutions also utilizes the Thomson-Reuters database. The characteristics are derived from the Fama-French 5-factor model, and include past 5-year stock CAPM beta, log book equity as a proxy for size, gross profitability, and asset growth. I further include the book-to-market ratio as the ratio of book equity to market cap from a year previous. As in Koijen and Yogo (2019), accounting characteristics are obtained as of at least 6 months and no more than 24 months prior to the given date in order to ensure the data are publically available at the time of portfolio formation.

Besides the Koijen and Yogo (2019) characteristics, in a robustness check I add to the set of stock characteristics dozens of financial ratios obtained from the Wharton Research Data Services financial ratios suite. I also obtain the quarterly and monthly series of shocks to Federal Reserve primary dealer capital introduced in He, Kelly, and Manela (2017) and available on Asaf Manela's website. As an additional intermediary variable I obtain the leverage of broker dealers introduced in Adrian, Etula, and Muir (2014).[13] The monthly Fama-French risk factors plus momentum factor are also downloaded from Ken French's website.

The sample construction proceeds as follows. Each quarter I take the intersection of the entire CRSP universe of stocks meeting share code and exchange code criteria described above with the Koijen and Yogo (2019) stock characteristics data, excluding any missing matches within a quarter. As done by many previous studies, I further exclude microcap stocks from the sample each quarter (defined to be stocks beneath the NYSE 20th percentile in market cap) and stocks with price less than $5 in order to focus on the set of stocks where large financial institutions are able to trade most freely. As is common practice, I additionally exclude financial stocks (stocks with SIC code between 6000 and 6999). This restriction is even more practical in my setting because the relationship between stock price

[13] Thanks to Koijen and Yogo (2019), He, Kelly, and Manela (2017), and Adrian, Etula, and Muir (2014) for making their data readily available.

movements and intermediary risk bearing capacity is highly endogenous for financial stocks. In terms of market cap, these restrictions drop a small portion of the CRSP equity universe– my sampling retains on average about 97% of total market capitalization of non-financial stocks on the CRSP tape. These stocks constitute the primary quarterly sample. I also convert the monthly Fama-French five factors and momentum to their respective quarterly versions. Unless otherwise noted, the sample period for regressions spans 1980q2 to 2017q3.

4 Empirical Strategy and Results

4.1 Constructing Measure of Intermediation

The characteristics-based extension on the model discussed in Appendix A suggests that stocks with similar characteristics but higher intermediary holdings should have higher betas on intermediary capital shocks. As such, I construct a measure of intermediation intended to be unrelated to key stock characteristics that proxy for information regarding cashflow distributions. Let $X_{i,t}$ be a vector of stock characteristics that are informative about the distribution of time $t+1$ cashflows of asset i. At each time t I run the following cross-sectional regression:

$$\text{Percent Intermediated}_{i,t} = \alpha_t + \beta_t X_{i,t} + \epsilon_{i,t} \tag{8}$$

In Appendix A I illustrate that the exact specification in (8) arises under a framework that expands upon my setting in section 2 and includes features very similar to the characteristics-based demand setting of Koijen and Yogo (2019). In particular, I show that if investors believe that the payoff covariance matrix can be decomposed into fundamental risk factor loadings that are linear in characteristics and the average asset payoffs are also linear in the characteristics, then (8) arises when households and institutional investors agree on the covariance matrix but households have some residual demand unrelated to the characteristics due to their different assessment of the first moment of asset payoffs. Under these assumptions, $\epsilon_{i,t}$ identifies a component of intermediary holdings that are due to variation in λ in the model and are uncorrelated with characteristics that provide information on the moments of asset cashflows. More broadly this approach is done to ensure that the cross-sectional spread in asset price response to intermediary risk bearing capacity shocks is not driven primarily by differential fundamental exposures to other risk factors.

If the risk tolerance of the financial institutions who are active in equity markets is time-varying and moves due to changes in empirical proxies of financial intermediary capital, sorting on $\epsilon_{i,t}$ should induce variation in betas on shocks to intermediary capital, and current intermediary capital should contain information about the expected returns of high $\epsilon_{i,t}$ assets relative to low $\epsilon_{i,t}$ assets. Specifically, high $\epsilon_{i,t}$ assets should have larger contemporaneous price response due to shocks to proxies for intermediary capitalization/intermediary risk tolerance and greater return predictability by the level of intermediary capital, as outlined in propositions 1 and 2.

Here Percent Intermediated$_{i,t}$ denotes the percentage of shares held by mutual funds, hedge funds, and other investment advisors. I focus on these institution types because they include the set of financial intermediaries that are the largest and most active in equity markets, though results are unaffected by additionally including any or all other 13F institutional investor types. One may also consider taking net positions by subtracting out aggregate short interest from Percent Intermediated$_{i,t}$. Average short interest on most stocks is small enough that this does not change my findings in any meaningful way, so I focus on just the long positions as presented on the 13F reports.

Regression equation (8) decomposes intermediary holdings into three components: $\beta X_{i,t}$, holdings due to firm fundamentals; α_t, holdings due to rise in average intermediation over time;[14] and, $\epsilon_{i,t}$, holdings unrelated to fundamentals (possibly reflecting households' unobserved expectations errors or perceived direct holding costs). In the empirical tests to follow I show in a variety of settings that $\epsilon_{i,t}$ is strongly related to intermediary capital betas on

[14] This has been well-documented. See Stambaugh (2014), for example.

both predictive and contemporaneous variables.

Implementing (8) requires that $X_{i,t}$ be strongly related to asset fundamentals that are informative about the distribution of future cashflows. Following Koijen and Yogo (2019), I focus on a set of stock characteristics derived from the Fama and French (2015) empirical asset pricing model that is known to have significant explanatory power for the cross-section of stock returns, and hence presumably provides considerable fundamental information regarding asset cash flows.[15] The empirical implementation of (8) includes the following set of stock characteristics in $X_{i,t}$: a second degree polynomial in log book equity; gross profitability to book equity; annual growth in firm assets (as a proxy for investment); book-to-market ratio using one-year lagged market cap; and, 5-year rolling monthly pre-ranking CAPM beta (requiring at least 24 observations to be included). These are derived from the sorting characteristics used to construct the risk factors in the Fama and French (2015) model. I use these characteristics as constructed by Koijen and Yogo (2019), who in turn construct them from Compustat so as to align with the procedure in Fama and French (2015).

In robustness checks I demonstrate that the set of characteristics included in (8) is not particularly important, so long as you control for stock size. My proxy for stock size is log book equity rather than market equity because market equity is a more endogenous equilibrium outcome that is affected by intermediary and household demand for the asset (in unreported regressions I find that findings maintain when using market equity instead of book equity for my size proxy). My model presented in section 2 demonstrates why it is important to control for stock size. The empirical tests described in propositions 1 and 2 require holding means and variances of underlying cashflows constant. Since I normalize net supply to one, the price of a given asset has the interpretation of the stock market cap and the means and variances are the means and variances of cashflows for owning the entire set

[15] Hou, Xue, and Zhang (2015) argue that their empirical asset pricing model, which is closely related to the model Fama and French (2015), performs particularly well in describing the cross-section of returns when micro-cap stocks are not over-weighted in portfolio formation. Thus (8) is likely to be more relevant among the set of the larger, more liquid stocks (non-micro cap stocks and stocks with share price above $5) that I consider in my analysis.

of shares for a given stock. Hence μ and Σ are highly dependent on the stock size.

In Table 1 I estimate the full-sample version of (8) with date fixed effects. By far the strongest predictor of intermediary holdings is stock size, as proxied by log book equity and log book equity squared, although each of the other characteristics is statistically significant in explaining institutional holdings. These institutions tend to overweight large stocks, profitable stocks, and stocks with high asset growth and CAPM betas, and tend to underweight value stocks. Note also that the R^2 is fairly high at .56, but still leaves a substantial portion of intermediary holdings unexplained, which unexplained portion I use to proxy for variation in the parameter λ (and hence θ_I, percent intermediated) from the model that is unrelated to stock fundamentals.

4.2 Empirical Results For Portfolios Sorted on Intermediation

Though theoretical propositions in section 2 required holding stock fundamentals constant, as a practical matter the empirical predictions in propositions 1 and 2 still hold as long as two assets look similar enough but have a wide spread in λ (and hence in percent intermediated). In terms of model parameters, if $\lambda_1 << \lambda_2$, $\mu_1 \approx \mu_2$ and $\sigma_1^2 \approx \sigma_2^2$, then the empirical implications of propositions 1 and 2 should still hold; namely, that asset 1 is much more intermediated than asset 2 and should have a higher beta on shocks to intermediary risk bearing capacity and should be more predictable by state variables capturing intermediary risk tolerance.

I organize around this idea in two ways: first, by forming equal-weighted portfolios on the quintiles of the residual institutional holding measure $\epsilon_{i,t}$ and then by running stock-level panel regressions interacting intermediary shocks with $\epsilon_{i,t}$. The portfolios are rebalanced quarterly. Figure 3 shows that the portfolio formation does quite well in holding characteristics constant while inducing variation in intermediation–the average institutional holdings quintile is just below five at each point in time for the top $\epsilon_{i,t}$ quintile portfolio, while it is just above one for the bottom $\epsilon_{i,t}$ quintile portfolio. Meanwhile the average quintile of the rest of the characteristics all hover around three for both portfolios. Thus these portfolios look almost exactly the same on key stock characteristics that form the basis of the Fama-French (2015) asset pricing model, which is known to describe well the cross-section of stock returns.

Table 2 shows the means and medians of stock characteristics for each of the five portfolios formed on quintiles of $\epsilon_{i,t}$, including percent holdings by mutual funds, hedge funds, and investment advisors; log of market and book equity; book-to-market ratio; asset growth; profitability/book equity; and pre-ranking CAPM beta estimated over the past 60 months (and a minimum of 24 months). In line with the graphical evidence in Figure 3, the means and medians of each characteristic besides percent intermediated are extremely close for the top- and bottom-quintile portfolios formed on $\epsilon_{i,t}$, and are also fairly close for the middle three portfolios (though they tend to have slightly higher profitability and book/market). Meanwhile there is a large spread in average percent intermediated between the top and bottom quintile portfolios, with 62% intermediated at the top and only 19% intermediated at the bottom. Thus Table 2 provides further confirmation that sorting on $\epsilon_{i,t}$ isolates variation in holdings by financial institutions while holding other stock fundamentals more or less constant, particularly when comparing the top and bottom quintile portfolios.

The top and bottom $\epsilon_{i,t}$ portfolios also have a high degree of comovement, as can be seen graphically in Figure 2. The correlation in excess returns on the two portfolios is 0.96. Table 3 shows the means, standard deviations, and Sharpe Ratios of the five portfolios formed on $\epsilon_{i,t}$. Focusing on the top and bottom quintiles, the annualized excess return standard deviations of 42.33% and 38.97% of the top and bottom quintile portfolios are also close to one another, as well as their Sharpe ratios, which are respectively 0.25 for the top quintile and 0.22 for the bottom quintile. As implied by the model (though not a highlighted feature), the top quintile portfolio has higher returns, though the spread is not very large at 1.868 percent per year and carries a t-stat of 1.880 that is marginally significant at the 10% threshold.

The model implies that the portfolios should have monotonically increasing exposures to shocks to intermediary risk bearing capacity. I use four proxies for this (from here I abbreviate the references to He, Kelly, and Manela (2017) and Adrian, Etula, and Muir (2014) as HKM and AEM, respectively): shocks to primary dealer market equity capital ratio from HKM; broker dealer book leverage shocks from AEM; value-weighted excess returns on the financial sector (stocks with SIC codes between 6000 and 6999); and, my primary proxy, which standardizes the HKM and AEM measures individually, takes the average of the two, and then standardizes this average to zero mean and unit variance.

The justification for combining the AEM and HKM shocks is to take a weighted average of financial sector risk-bearing capacity using the most prominent proxies proposed in the literature, analogous to Haddad and Muir (2018). Moreover, Ma (2019) demonstrates that a heterogeneous intermediary SDF can be constructed as a function of shocks to two state variables that are closely related to the AEM and HKM measures. This SDF arises when different classes of intermediaries face heterogeneous financial constraints or have different risk aversion, and yields leverage patterns that are simultaneously consistent with the findings of both HKM and AEM.[16] I further include returns on the financial sector, as this measure is directly related to the wealth share shocks that are important in equity-constraint based intermediary asset pricing models.

I test proposition 1 by running regressions of the form

$$R^e_{i,t+1} = \alpha_i + \beta_{1,i} F_{t+1} + \beta_{2,i}(\mathrm{Mkt}^{NonFin}_{t+1} - R_{f,t}) + \nu_{i,t} \tag{9}$$

individually for F_{t+1} = Intermediary Shock_{t+1}, Capital Shock_{t+1}, Leverage Shock_{t+1}, and Ex Ret. $(\text{Fin})_{t+1}$ and also for i equal to the excess returns over the risk free rate for the five intermediation ($\epsilon_{i,t}$) quintile portfolios and the high minus low $\epsilon_{i,t}$ spread portfolio. Here Intermediary Shock_{t+1} refers to the combined AEM and HKM measure; Capital Shock_{t+1} represents the HKM shock; Leverage Shock_{t+1}, the AEM shock; and finally, Ex Ret. $(\text{Fin})_{t+1}$,

[16]HKM find that bank holding companies have countercyclical leverage, while AEM finds that broker-dealers have procyclical leverage.

the excess return on the financial sector. I control for a version of the value-weighted market risk factor that includes just the returns to nonfinancial stocks. I include this control for several reasons. First, the AEM and HKM models present asset pricing tests controlling for market risk. Second; as illustrated in equation (6), it's important to control for shocks that could proxy for changes in the risk aversion of households, and market returns relate to time-variation in risk-aversion for certain classes of models, such as in a habit model. The joint inclusion of shocks to intermediary risk bearing capacity and non-financial stocks also directly relates asset price movements to financial and non-financial wealth share shocks. The non-financial market risk factor has a correlation of 0.99 with the value-weighted market risk factor from Ken French's website.

Table 4 shows the results of the contemporaneous portfolio tests using the combined Intermediary Shock_{t+1} measure. The same findings are illustrated graphically in Figure 4. Strikingly, there is a strong monotonically increasing relationship in the betas on the intermediary shock and no pattern whatsoever in the non-financial market return betas. The t-stat of 4.45 on the quintile 5 minus quintile 1 intermediation spread portfolio is highly significant. This monotonic pattern is directly in line with the theoretical implications presented in section 2 and also with He and Krishnamurthy (2018), who show that shocks to intermediary risk tolerance for similar but more intermediated assets should have relatively higher betas on intermediary risk tolerance shocks than on household wealth shocks. Since the intermediary shock is scaled to unit standard deviation and returns are in annualized percent form, the coefficient of 4.13 in column (6) of Table 4 means that the return on the high intermediation portfolio increases by 4.13% relative to the low intermediation portfolio on an annualized basis in response to a one-standard deviation intermediary shock.

The empirical patterns illustrated in Figure 4 continue to hold when examining each individual proposed intermediary shock. Figure 5 demonstrates this. Loadings are increasing from bottom to top quintile and the top minus bottom quintile spread has a significant loading for each of the four intermediation risk bearing capacity shocks. The exposures increase monotonically for all measures. Note also that combining the information in AEM leverage shocks and HKM capital shocks leads to a more significant coefficient on the top minus bottom quintile spread.

As a final piece of evidence for the contemporaneous portfolio regressions, in Figure 6 I run regressions separating the HKM capital shocks and AEM leverage shocks within the same specification:

$$R^e_{i,t+1} = \alpha_i + \beta_{1,i} F_{t+1} + \beta_{2,i}(\text{Mkt}^{NonFin}_{t+1} - R_{f,t}) + \nu_{i,t} \tag{10}$$

The high minus low intermediation excess return is significantly positive for both risk factors, with monotonicity in betas for both the capital shocks and the leverage shocks. Thus the HKM capital and AEM leverage factors continue to display patterns in line with proposition 1 when included together in the same regression.

I next turn to my predictability tests that relate to proposition 2, which is that otherwise similar but more intermediated stocks should have excess returns that are more negatively (positively) predictable by state variables that represent higher (lower) risk-bearing capacity of financial institutions. To do this, I run regressions of overlapping quarterly high minus low $\epsilon_{i,t}$ excess returns at the monthly frequency on a set of intermediary state variables. Regressions take the following form:

$$R^{Q5}_{t\to t+3} - R^{Q1}_{t\to t+3} = \alpha + \beta_1 X_t + \beta_2 Z_t + \nu_t \tag{11}$$

Here X_t represents any of my proxies for state variables related to time t risk tolerance of intermediaries and Z_t is a set of control predictors. Following HKM, I use the squared market leverage of Federal Reserve primary dealers as a predictor. HKM show that the conditional risk premium is a nonlinear function of the underlying capital ratio state variable, which is proportional to $(1/\text{capital ratio})^2$ in a simplified version of the He and Krishnamurthy (2013) model. Since this variable relates to lower risk tolerance of intermediaries, it should predict returns with positive sign. In predictability tests HKM also point out that the theory of AEM implies that the broker-dealer leverage ratio should predict returns negatively, so I use this as a second state variable. In line with the contemporaneous regressions, my primary predictor is a combined state variable that takes the average of the standardized squared primary dealer leverage and the negative of the standardized broker dealer leverage. I label this combined state variable η. I also use the squared primary dealer leverage and broker dealer leverage individually, as well as the share of stock market wealth held by financial stocks as my final proxy for X_t in equation (11) above. To be in agreement with theory, the financial sector wealth variable should predict high minus low intermediation portfolio excess returns with negative sign, as a high wealth share state corresponds with higher risk tolerance.

I also control for several return predictors from the literature. I obtain the cyclically-adjusted price to earnings ratio from Robert Shiller's website and the consumption-wealth ratio ("cay") from Lettau and Ludvigson (2001) from Sydney Ludvigson's website. I also add the 10-year minus 3-month t-bill rate term spread as a control in the predictive regressions and the investor sentiment measure from Baker and Wurgler (2006) obtained from Jeffery Wurgler's website. I include cay and sentiment as potential proxies for household willingness to take risk. The cyclically-adjusted price/earnings ratio are included because of their common use as leading indicators of aggregate macroeconomic conditions and as return predictors. Because the broker-dealer leverage ratio and the consumption/wealth ratio are available quarterly I hold them constant within a quarter for each month in the sample, but I use the monthly versions for the the rest of the predictors. Due to autocorrelation induced by overlapping observations I compute standard errors using the method of Newey-West with 4 lags.[17] Table 5 shows the regressions for the combined state variable (labeled "η"), while Tables 6 and 7 present the same results using the HKM/AEM predictors separately

[17] The standard errors on the coefficients of interest tend to decrease when including more lags than this, so I choose 4 as the lag length to be conservative, while still correcting for the autocorrelation from overlapping observations.

and the financial sector wealth share, respectively.

The predictability tests support proposition 2–in each case the proxy for intermediary risk tolerance has the appropriate sign and is statistically significant in predicting the quarterly returns on the high minus low intermediary ownership (high minus low $\epsilon_{i,t}$) portfolio excess returns, with t-stats hovering just above or below 3 depending on the specification. The R^2 of η in predicting the quarterly high-minus low intermediation portfolio return is 4%. The inclusion of the other predictors actually enhances the power of η to predict the spreads, as the highest t-stat on η attains in the last column where all predictors are included.

Note also that the other predictors all enter with statistically insignificant sign, except for the cyclically adjusted price to earnings ratio ("P/E") in the last column, which is significant at the 10% level with positive sign. As will be demonstrated in the next section, this positive sign disagrees with the negative coefficient on this variable in the stock-level analysis. The only predictors that demonstrate consistently strong predictive performance for the high minus low intermediation spread return across all specifications are those related to the health of financial intermediaries.

Since excess returns are expressed in annualized percentage terms in these regressions and predictors are standardized, the coefficients in row 1 of Table 5 imply that a one-standard deviation increase in η (i.e. a decrease in intermediary risk tolerance) translates into a roughly 3-6% increase in expected returns going forward for the top intermediated quintile portfolio over the bottom quintile portfolio. Similar magnitudes are estimated in Tables 6 and 7. Table 6 demonstrates that the predictability of the high minus low intermediation portfolio maintains when separating the HKM/AEM predictors, with the two having the appropriate positive and negative signs, respectively. Meanwhile Table 7 shows that the financial stock market wealth share significantly predicts the spread with negative sign in all specifications, consistent with theoretical models where intermediaries are less constrained when their wealth share is high.

As discussed in section 2, the combined presence of greater return return predictability and outsize price movements to contemporaneous shocks is important for empirically testing the theory. The loadings on shocks should come because of movements in discount rates; since the price response to both the pre-determined level of and the growth rate in the state variables is larger in the more intermediated portfolio, this supports the discount rate channel as the driving force behind these patterns.

I include a final test to examine the presence of a theoretical mechanism in the cross-section of return predictability outlined in Gromb and Vayanos (2018). In their model when the capital of constrained arbitrageurs depletes, the expected returns increase relatively more on the assets where arbitrageurs take larger positions. This causes the increased spread to self-correct over time as intermediary capital recovers due to the increased expected returns on their positions. To test for such effects, I run regressions of the form

$$R^{Q5}_{t+k} - R^{Q1}_{t+k} = \alpha + \beta_k \eta_t + \nu_t \tag{12}$$

where t is at the monthly horizon and k varies from 1-month ahead to 18-months ahead. Figure 7 plots $\widehat{\beta_k}$ and its 90% confidence interval as well as the R^2 for $k = 1, ..., 18$. As implied by the theory, the coefficients $\widehat{\beta_k}$ decrease with k, as does the R^2. Thus the quarterly horizon used in the previous predictability tests from this section features much of the overall high minus low intermediation portfolio spread return predictability of η_t. This is consistent with temporary relative asset price distortions that are corrected over time as constraints on intermediaries relax when capitalization improves, in line with Gromb and Vayanos (2018), and more broadly with models where intermediary capital moves slowly because of constraints that become more binding when intermediaries are poorly capitalized.[18]

[18]See for example Duffie (2010) for a theoretical summary and Mitchell, Pedersen, and Pulvino (2007) for early empirical evidence in convertible bond markets, or more recently Siriwardane (2019) in credit default swap markets.

4.3 Stock-Level Panel Regressions

This section demonstrates that the portfolio-level evidence from the previous section extends to the individual stock level. My stock level empirical tests take the following form for the contemporaneous regressions:

$$R_{i,t+1} - R_{f,t} = \alpha_0 + \beta_1 F_{t+1} \times \epsilon_{i,t} + \beta_2 W_{t+1} \times \epsilon_{i,t} + \alpha_t + \alpha_i + \nu_{i,t+1} \tag{13}$$

Here F_{t+1} is any of the contemporaneous shocks to intermediary risk tolerance. Finding $\beta_1 > 0$ implies that betas on shocks to financial institutions increase with the component of intermediary holdings that is uncorrelated with characteristics of the stock. Thus for the contemporaneous shocks used in the previous section $\beta_1 > 0$ is in line with the theory. I control for value-weighted non-financial market excess returns and also add specifications that include the Fama-French (2015) factors plus the momentum factor for W_{t+1} in (13). I also add time fixed-effects to control for common shocks to the cross section as well as including stock fixed effects. Replacing the time fixed effects with uninteracted risk factors yields estimates that are essentially identical.

Once again agreeing with the theory, Table 8 shows that $\beta_1 > 0$ for all intermediary shocks considered and is strongly significant for all specifications except in the case of the AEM leverage shocks, which show consistent positive sign but have p-values that are significant at just the 10% level for each of the specifications. However, note in the first row of Table 8 that the intermediary shocks which combines the information embedded in the AEM and HKM factors yields a much stronger estimate than just including the HKM or AEM factors alone. The financial sector excess return provides more evidence in agreement with the theory, as it also has positive and significant coefficient on the residual intermediation interaction term across specifications.

The economic magnitude of these estimates are fairly large. Consider two stocks with the exact same characteristics, except one is entirely owned by mutual funds/hedge funds/investment advisors, and the other is owned entirely by households. Looking at the coefficients in the first row of Table 8, the returns to the fully intermediated stock increase by 8-10% per year relative to the unintermediated stock on an annualized basis in response to a one-standard deviation shock to the HKM/AEM averaged intermediary factor. Point estimates on these coefficients are also quite precise, with t-stats ranging from 4.6 to 5.3.[19]

The only included non-intermediary risk factor whose betas significantly increase with $\epsilon_{i,t}$ is the Fama-French robust minus weak profitability factor. This feature is also present in portfolio regressions where I control for the Fama-French (2015) factors plus momentum in the section 4.4, though I don't explicitly report the coefficient estimates in those specifications. The reason for this increased exposure to the profitability factor is not immediately clear, though I find in unreported regressions that the addition of the profitability factor increases the magnitude and significance of the coefficients on the intermediary risk factors. It's also important to note that my model does not preclude the possibility that other risk factors have increasing exposure across level of intermediation Still, this case is interesting because I have already averaged out stock-level profitability. It is possible that intermediary marginal utility loads more on the profitability factor relative to households, though such an investigation is out of the scope of this paper.[20]

Next I perform stock-level predictive regressions, which are specified as

$$R_{i,t+1} - R_{f,t} = \alpha_0 + \delta_1 X_t \times \epsilon_{i,t} + \delta_2 Z_t \times \epsilon_{i,t} + \alpha_t + \alpha_i + \nu_{i,t+1} \tag{14}$$

For the predictive panel regressions δ_1 should be less than zero for broker dealer squared leverage and the financial sector wealth share and should be positive for primary dealer squared leverage and the combined predictor η. I include the same controls for Z_t in the predictive regressions as in the portfolio regressions from the previous section. As in the

[19]Standard errors are clustered by date to account for cross-sectional correlation in the residuals and are also adjusted for one lag of autocorrelation.

[20]In a previous working version of the paper, Cho (2019) argues that the capital of arbitrageurs such as hedge funds loads positively on the RMW profitability factor.

contemporaneous regressions I include time and stock fixed effects.

Table 9 paints a similar picture for the predictive regressions for individual stocks as in the portfolio level analysis from the preceding section. Interaction terms on the combined state variable η are strongly positive across specifications, as is primary dealer squared leverage. Significantly negative coefficients obtain on the broker dealer leverage and financial sector wealth share interactions with $\epsilon_{i,t}$, in accordance with the theory and the empirics in the previous section. Meanwhile, alternative predictors don't seem to have predictability that relates strongly with intermediation, except in the case of the cyclically-adjusted price to earnings ratio, which has negative sign and is significant in the specification in column 6. However, recall that the "P/E" coefficient in the portfolio regressions had an opposite positive sign, so that the estimates for the cyclically-adjusted price to earnings ratio are inconsistent across portfolio and stock-level settings. Meanwhile the intermediary state variables have statistically significant coefficients with consistent signs across specifications, and have comparable magnitudes as well.

To put the predictability regressions in economic terms, once again consider the hypothetical stock that is entirely owned by mutual funds/hedge funds/other investment advisors relative to a stock owned entirely by households but with the same characteristics. The first row of Table 9 implies that the intermediated stock has a risk premium that is 11 to 12% on an annualized basis higher relative to the unintermediated stock when η increases by one standard deviation.

For a final stock-level test, I examine the relationship between residual intermedation $\epsilon_{i,t}$ and rolling stock betas on intermediary shocks. I first compute rolling betas for each stock i and each intermediary shock:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \mathrm{F}_t + \beta_i^M \left(\mathrm{Mkt}_t^{NonFin} - \mathrm{Rf}_t\right) + \delta_{i,t}$$

individually for $F =$ Capital Shock, Leverage Shock, Intermediary Shock, and Ex Ret (Fin).

The parameter β_i, t is estimated at each time t using a rolling window of plus or minus 15 quarters, including the given quater. I then run the panel regression

$$\widehat{\beta}_{i,t-15\to t+15} = \alpha_0 + \beta_1 \epsilon_{i,t} + \beta_2 Z_{i,t} + \alpha_t + \alpha_i + \nu_{i,t} \tag{15}$$

The controls $Z_{i,t}$ include profitability, investment, CAPM beta, book/market, second-degree polynomial in log market cap and log book equity, in addition to stock and time fixed effects. I require the estimated betas to have at least 20 observations in order to include the observation in (15). Because of the overlapping windows I double cluster the standard errors by stock and time. Table 10 shows that the individual stock betas centered around time t on each of the intermediary shocks are each strongly increasing intermediation measure $\epsilon_{i,t}$, with t-stats ranging from 2.67 to 3.85. Thus the component of intermediary holdings unrelated to characteristics has strong explanatory power for time-variation in betas even at the individual stock level. The coefficient of 6.7 on $\epsilon_{i,t}$ in column 1 for the combined AEM/HKM intermediary shock is comparable (albeit slightly lower) to the magnitudes found in Table 8 and has the interpretation that, holding stock characteristics constant, the return response of a completely intermediated stock to a one-standard deviation intermediary shock is 6.67 percentage points higher on an annualized basis relative to a comparable but completely household-owned stock.

4.4 Additional Tests and Robustness

A natural question arises on whether or not results depend crucially on the characteristics included in, or excluded from, the regression (8) to back out the residual intermediation component $\epsilon_{i,t}$. Though this can't be ruled out perfectly, I examine the empirical robustness of my findings to the inclusion of many more characteristics or alternatively to just controlling for size. To do this, I download the set of stock financial ratios provided by the Wharton Research Data Services Financial Ratios Suite. This set of stock characteristics was used previously by Kozak, Nagel, and Santosh (2019) to construct a stochastic discount factor from a large number of potential cross-sectional return predictors.

Though I obtain the full set of 73 financial ratios from WRDS, I restrict the set of characteristics to 40 out of the 73 due to data availability restrictions that I impose.[21] Using the categories provided by WRDS, the 40 ratios that remain comprise 6 valuation ratios, 13 profitability ratios, 4 capitalization ratios, 7 financial soundness ratios, 3 solvency ratios, 3 efficiency ratios, and 4 other ratios. I supplement the original set of characteristics included in (8), which consisted of a second degree polynomial in log book equity; gross profitability to book equity; annual growth in firm assets; book-to-market ratio using one-year lagged market cap; and, 5-year rolling monthly pre-ranking CAPM beta (requiring at least 24 observations to be included) with these 40 financial ratios and examine if including the additional characteristics substantially changes anything. On the other end, I also check the robustness of my results to the inclusion of just the second degree polynomial in log book equity. Using these alternative sets of characteristics I re-estimate $\epsilon_{i,t}$ and re-form the quarterly quintile portfolios.

Further robustness checks include value-weighting the portfolios using one-year lagged market cap (and which uses value-weighted cross-sectional regressions to back out $\epsilon_{i,t}$); dropping the financial crisis from the sample (defined using the dates calculated by the NBER as beginning after the business cycle peak in the end of the fourth quarter of 2007 and ending after the business cycle trough in the second quarter of 2009); and, controlling for the Fama-French factors plus momentum as in the stock-level panel regressions from the last section. The contemporaneous regressions are found in Table 11 and the predictive regressions are in Table 12. Table 11 uses my primary proxy for contemporaneous shocks to risk bearing capacity, the "Intermediary Shock" (which is the average of the standardized AEM/HKM shocks). Meanwhile in the Table 12 predictive regressions, I focus on the state variable η, which is my main proxy for the time t risk bearing capacity and is constructed

[21] I outline the process I use for selecting these characteristics in detail in Appendix C.

as the average of the standardized primary dealer squared leverage ratio and the negative of standardized broker-dealer leverage. The tables report regression coefficients for the high minus low intermediation quintile spread portfolio.

Table 11 demonstrates that the intermediary shock significantly explains the spread in returns between high and low residual intermediation portfolios no matter the specification or the set of characteristics included. Interestingly, without controlling for the other characteristics the non-financial market risk factor also strongly loads on the returns to the spread portfolio, but this is not the case in any of the other specifications. Value-weighting changes little, nor does controlling for the Fama-French (2015) risk factors plus the momentum factor. In the last column we do see that both dropping the financial crisis and including the additional risk factors increases estimation noise substantially and reduces the t-stat on the intermediary shock to 1.75. Still, testing the theoretical prediction that the loading is positive entails a one-tailed rather than a two-tailed test, which would still imply significance at the 5% level for this coefficient. The point-estimates for both specifications excluding the crisis are also lower, suggesting that the financial crises was an important event in determining the endogenous covariance with shocks to intermediaries, and points to the magnified effects of shocks to risk-bearing capacity during times when intermediaries were likely financially constrained, consistent with features in the constrained regions of the models of He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014).

The predictive regressions in Table 12 have the same features. Increasing η (or decreasing intermediary risk tolerance) predicts higher returns going forward on the top intermediation portfolio relative to the low intermediation portfolio. As in Table 11, the specification which only includes log book equity features more significant coefficients on the control predictors, but this almost entirely goes away in the other specifications. The coefficient on η remains quite stable, strongly significant, and positive for all specifications, with value-weighting portfolios, including more stock characteristics, or dropping the crisis hardly affecting the estimates nor the significance. Interestingly, the coefficient on η goes up a bit in the specification that drops the financial crisis, though the estimation error does increase and the predictability as measured by the R-squared decreases, from 8.7% to 7.5%.

While one can never account for all information regarding a stock, Tables 11 and 12 illustrate that the empirical patterns are robust to conditioning on a wide range of characteristics so long as stock size is taken into account. It should also be noted that unobserved characteristics would tend to bias against finding an effect. This is because stocks whose cashflows have naturally higher covariance with shocks to intermediaries provide very poor hedges against bad times for financial institutions, and so observed holdings are unlikely to be driven by some underlying institutional preference for high-intermediary shock beta stocks. Thus unobserved stock information would tend to result in understating rather than overstating these effects.

5 Discussion of Empirical Results

Given the empirical facts presented, a brief discussion is in order on why the risk bearing capacity of financial institutions whose holdings I include (mutual funds, hedge funds, and other investment advisors) depends on shocks to bank holding companies of Federal Reserve Primary dealers and the broker-dealer sector in general. The connection for hedge funds is more readily apparent, as hedge funds are levered institutional investors who depend heavily on capital provision by dealer banks for their ability to trade actively in equity markets. For example, Aragon and Strahan (2012) list the top prime brokers to hedge funds in the years 2002-2008 leading up to the financial crisis; the vast majority of the top ten institutions and all of the top five each year were also Federal Reserve primary dealers at the time. Cho (2019) also argues that hedge fund capital depends on the AEM broker-dealer leverage. When these institutions become distressed, capital availability declines and hedge funds in turn also become distressed. In line with this, Ben-David, Franzoni, and Moussawi (2011) demonstrate that hedge funds were forced to delever when their institutional capital providers withdrew capital via margin calls and redemptions.

Ben-David, Franzoni, and Moussawi (2011) show that mutual funds also suffered redemptions in the crisis period but they were not as severe as those of hedge funds. Since most mutual funds do not use leverage, they are not as dependent on levered institutions such as dealer banks for obtaining capital. However, there are a few reasons to believe that mutual funds' ability to trade may be impeded when levered dealer banks/broker dealers and hedge funds become distressed. When dealer banks reduce their exposure to equity markets, whether directly through their trading desks or indirectly by seeking redemptions from hedge funds, mutual funds lose natural counterparties to their trades when market liquidity dries up. Thus as argued in He and Krishnamurthy (2013), in a liquidiation crisis the distress of levered institutions may be the most relevant for determining price movements.

In line with this argument, Nagel (2012) documents that returns to liquidity provision in equity markets dramatically spiked during the financial crisis as levered financial institutions in distress required high price concessions in return for offering liquidity. As mutual funds represent the largest class of institutional investors in equity markets, and entering and exiting positions requires shifting large amounts of capital. Consequently mutual funds' ability to trade in equity markets is likely to be highly dependent on the health of levered institutions who supply market liquidity for their trades, even if they directly obtain most of their investment capital from households rather than dealer banks/broker-dealers. Moreover, as noted by Gompers and Metrick (2001), the distribution of asset managers in the 13F data is highly skewed so that the holdings are dominated by a relatively small set of very large institutional investors. These investors with large concentrated positions are likely to value market liquidity much more relative to small and dispersed individual retail investors whose trades are comparably miniscule in size.

Yet another more direct connection with the health of dealer banks/broker-dealers for at least some mutual funds and investment advisors comes from the fact that dealer banks/broker-dealers often directly operate equity-focused funds through asset management subsidiaries whose holdings would be classified under mutual funds or investment advisors in the 13F data. In fact, nearly every historical Federal Reserve primary dealer in the post-1980 period has a subsidiary fund manager in the 13F data that is identified as a mutual fund or investment advisor using the Koijen and Yogo (2019) corrected type codes. Hence shocks to their bank holding companies would likely have directly diminished the willingness of such funds to take risk via internal capital markets.

The empirical facts that are documented in this paper are all broadly in accord with the mechanisms detailed above. As explained in proposition 3 of section 2, unless household risk tolerance shocks are negatively correlated with risk tolerance shocks of mutual funds/hedge funds/investment advisors, increasing price responses to intermediary shocks along the dimension of increased intermediation *must* come because these institutions' ability to take on risk is affected by these shocks. From this perspective, my findings suggest that the largest institutional investors in equity markets do indeed care about shocks to dealer banks and other broker-dealers, and the above discussion merely provides an explanation as to why this could be.

6 Conclusion

Building off of theoretical and empirical work that features constrained intermediaries as marginal investors, I show that the asset holdings of financial institutions generate higher covariances of more intermediated stocks with shocks to intermediary risk bearing capacity via movements in discount rates. After accounting for stock fundamentals, stocks that are held more by intermediaries covary more with shocks to intermediaries' ability to take on risk, and state variables capturing the health of financial intermediaries predict better the returns of the more intermediated stocks than the less intermediated stocks, again conditional on stocks having similar characteristics. These effects are large in economic magnitude, implying that two alike stocks would have conditional risk premia that are 11-12% higher if owned entirely by financial institutions instead of households when a proxy for intermediary risk tolerance decreases by one standard deviation. Furthermore, the beta on shocks to intermediary risk bearing capacity on a portfolio formed on the most intermediated stocks is more than 5 times higher than the beta on the least intermediated portfolio, despite the two portfolios having stocks of about the same size, book/market, investment (asset growth), profitability, and CAPM betas.

Previous empirical papers testing frictional intermediary asset pricing theories have tended to focus on asset markets that are comparatively difficult for households to access. By contrast, I demonstrate that effects predicted by intermediary asset pricing models persist even among equities, which is perhaps the easiest asset class for households to directly access. In this sense the findings in this paper may provide a lower bound for the relative importance of intermediary asset pricing in other asset classes.

The empirical evidence presented in this paper suggests that even the risk bearing capacity of large institutional investors who tend to avoid taking on leverage, such as mutual funds, still depends on the health of levered dealer banks. Accordingly, future research may examine this connection in more depth, including quantifying how much the ability of large institutional investors to trade or bear risk in equity markets directly depends upon the liquidity provision of levered institutions such as dealer banks, broker-dealers, and hedge funds.

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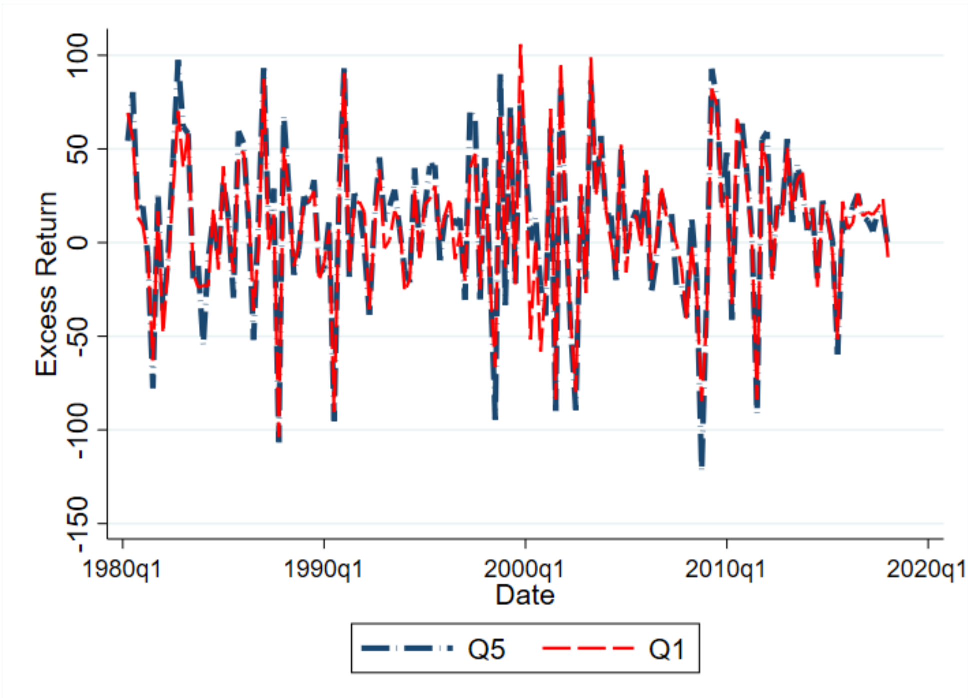
Figures

Figure 2: **Annualized Excess Return For Top and Bottom Intermediation ($\epsilon_{i,t}$) Quintile Portfolios**

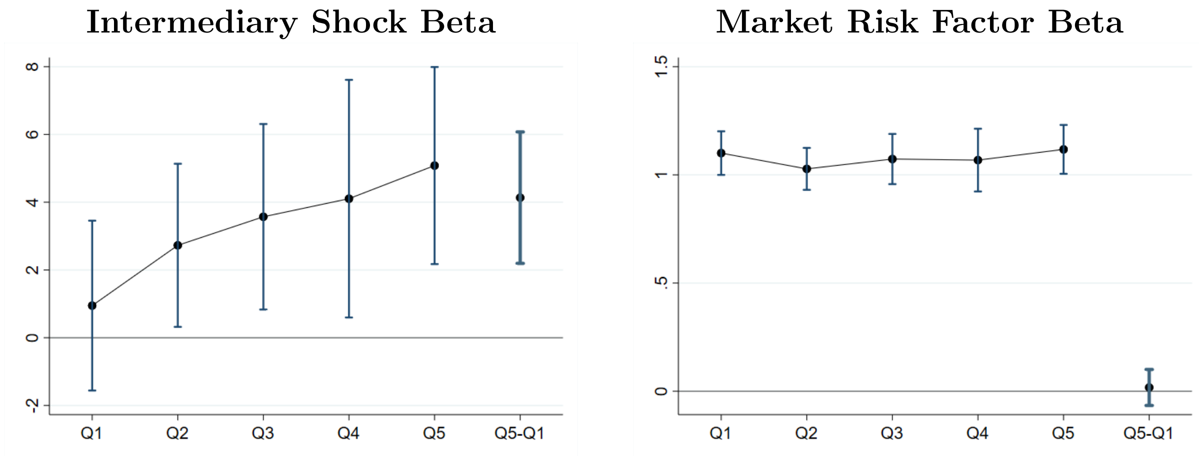


This figure shows the time series of annualized quarterly excess returns on the top and bottom quintile equal-weighted portfolios formed on the intermediation measure $\epsilon_{i,t}$. Details on the construction of $\epsilon_{i,t}$ are presented in section 4.1. Sample spans 1980q2 to 2017q3.

Figure 3: **Average Quintile of Given Characteristic For Top and Bottom Intermediation ($\epsilon_{i,t}$) Quintile Portfolios**

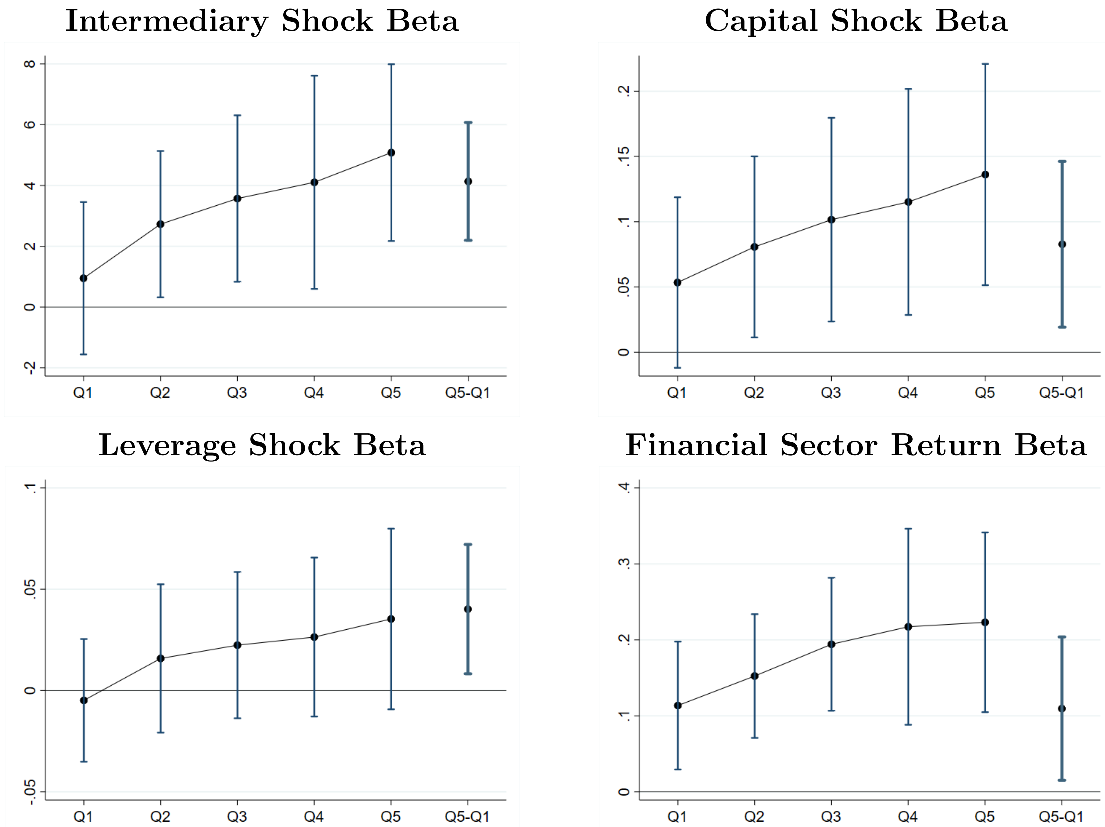
This figure shows average the quintiles over time for given characteristics for top and bottom quintile equal-weighted portfolios formed on the intermediation measure $\epsilon_{i,t}$. Details on the construction of $\epsilon_{i,t}$ are presented in section 4.1. Sample spans 1980q2 to 2017q3.

Figure 4: **Coefficients on Intermediary Shocks and Market Risk Over Portfolios Formed on Intermediation Quintile**



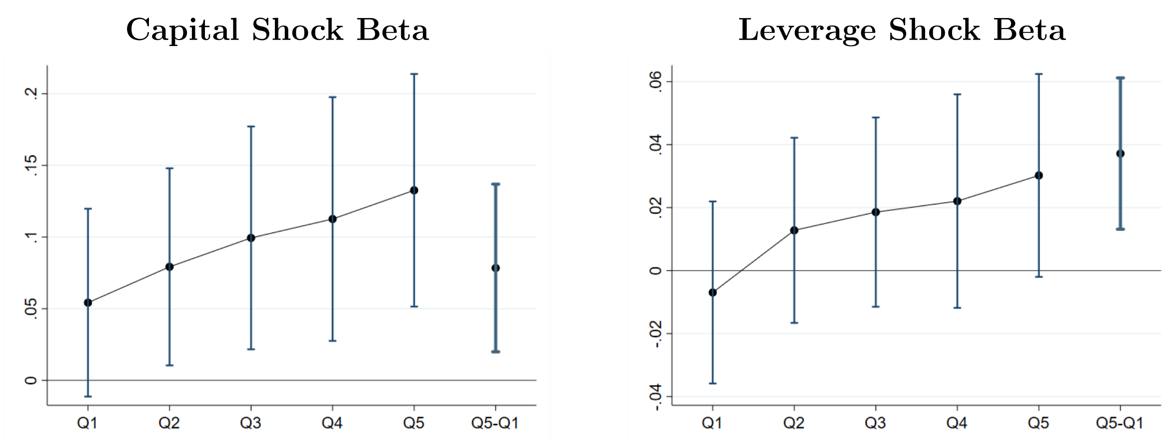
This figure plots regression coefficients as in (9) of the main text. The figure on the left shows the coefficient estimates on the average of the standardized Federal Reserve primary dealer equity capital ratio shocks from He, Kelly, and Manela (2017) and the broker-dealer book leverage growth shocks from Adrian, Etula, and Muir (2014) for five portfolios formed on the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail), as well as the coefficient on the intermediary shocks for the top minus bottom quintile spread. The figure on the right shows the corresponding betas on a version of the value-weighted market risk factor that excludes returns on financial stocks (SIC code between 6000 and 6999). The confidence bands represent 95% confidence intervals computed from Newey-West standard errors. The Intermediary Shock measure is standardized and returns are in annualized percent form. Sample spans 1980q2 to 2017q3.

Figure 5: **Betas On Portfolios Sorted By Intermediation on Different Shocks To Intermediary Risk Bearing Capacity**



This figure presents regressions estimates as in (9) of the main text for each of the proposed intermediary shocks for each of the five portfolios formed on quintiles of the intermediation measure $\epsilon_{i,t}$ constructed in section 4.1 of the main text, as well as the top minus bottom quintile portfolio spread. The capital and shocks refer to the Federal Reserve primary dealer equity capital ratio shocks proposed in He, Kelly, and Manela (2017), while the leverage shocks refer to the broker-dealer leverage shocks from Adrian, Etula and Muir (2014). Intermediary shock refers to the average of the standardized leverage and capital shocks. Financial sector return is the value-weighted return on the financial sector (stocks with SIC code between 6000 and 6999). Regressions control for a version of the value-weighted market risk factor that excludes financial stocks. The Intermediary Shock measure is standardized and returns are in annualized percent form. Error bands represent 95% Newey-West confidence intervals. Sample spans 1980q2 to 2017q3.

Figure 6: **Betas On Portfolios Sorted By Intermediation On Capital and Leverage Shocks Included in Same Specification**

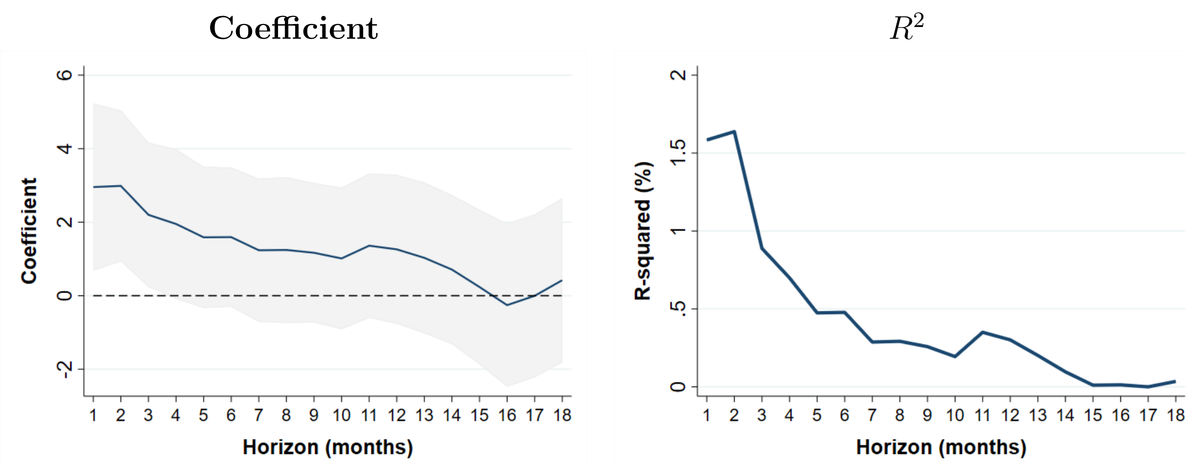


This figure presents regressions estimates as in (10) of the main text:

$$R_t^e = \beta_{0,i} + \beta_{1,i}\text{Capital Shock}_t + \beta_{2,i}\text{Leverage Shock}_t + \beta_{3,i}\left(\text{Mkt}^{NonFin} - \text{Rf}\right)_t + \epsilon_{i,t}$$

This plots show betas on capital and leverage shocks included together in the same specification and for each of the five portfolios formed on quintiles of the intermediation measure $\epsilon_{i,t}$ constructed in section 4.1 of the main text, as well as the top minus bottom quintile portfolio spread. The capital shocks refer to the Federal Reserve primary dealer equity capital ratio shocks proposed in He, Kelly, and Manela (2017), while the leverage shocks refer to the broker-dealer leverage shocks from Adrian, Etula and Muir (2014). Error bands represent 95% Newey-West confidence intervals. Sample spans 1980q2 to 2017q3.

Figure 7: **Predictability of One Month High Minus Low Intermediation Spread Portfolio Returns On Intermediary Risk Bearing Capacity At Different Monthly Horizons**



This figure shows coefficients obtained from predictive regressions of the one month high minus low return spread for portfolios formed on top and bottom quintiles of intermediation measure $\epsilon_{i,t}$ (which is constructed in section 4.1 of the text) on predictor η_t at different monthly horizons. Regressions are of the form

$$R_{t+k}^{Q5} - R_{t+k}^{Q1} = \alpha + \beta_k \eta_t + \nu_t$$

as in equation (12) in the main text. The horizon k varies from 1 month to 18 months. The predictor η_t is the average of the standardized primary dealer squared leverage from He, Kelly, and Manela (2017) and the negative of standardized broker dealer leverage from Adrian, Etula, and Muir (2014). The gray shaded area corresponds to 90% Newey-West confidence intervals with one lag.

Tables

Table 1: **Panel Regression of Percent Stock Ownership By Intermediaries on Stock Characteristics**

	Percent Intermediated$_{i,t}$
Log Book Equity	0.086***
	(17.13)
Log Book Equity Sq.	-0.0070***
	(-16.94)
Profitability	0.024***
	(2.73)
CAPM Beta	0.035***
	(9.33)
Asset Growth	0.035***
	(6.32)
Book/Market	-6.25**
	(-1.99)
Stock Fixed Effects	Yes
Observations	214448
R^2	0.56

This table shows estimates of the full sample version of the cross-sectional regression in (8):

$$\text{Percent Intermediated}_{i,t} = \alpha_0 + \alpha_t + \beta X_{i,t} + \epsilon_{i,t}$$

for stocks included in the sample. At each time t the top 1% of observations of Percent Intermediated$_{i,t}$ are winsorized to deal with clear outliers in cross section of institutional holdings. Standard errors are clustered by stock i and quarter t and corresponding t-stats are in parentheses. Quarterly fixed effects pick up variation due to the rise over time in average intermdiation. The sample ranges from 1980q2 to 2017q3.

Table 2: **Summary Statistics of Stock Characteristics For Portfolios Sorted on Quintiles of Intermediation Measure** $\epsilon_{i,t}$

Panel A: Portfolio Characteristic Means

	% Inst	Log(ME)	Log(BE)	BE/ME	Asset Growth	Prof/BE	CAPM β
Q1	.2	6.84	6.16	.88	.14	.22	1.17
Q2	.34	7.22	6.52	.92	.12	.23	1.11
Q3	.43	7.25	6.54	.92	.12	.23	1.16
Q4	.51	7.14	6.43	.87	.13	.23	1.18
Q5	.62	6.92	6.16	.88	.14	.21	1.18

Panel B: Portfolio Characteristic Medians

	% Inst	Log(ME)	Log(BE)	BE/ME	Asset Growth	Prof/BE	CAPM β
Q1	.17	6.7	5.82	.79	.14	.22	1.17
Q2	.32	7.19	6.24	.83	.12	.23	1.09
Q3	.42	7.26	6.28	.82	.12	.23	1.13
Q4	.52	7.14	6.2	.8	.13	.23	1.17
Q5	.65	6.93	5.86	.82	.14	.22	1.19

This table shows the means and medians of percent holdings by institutional investors (mutual funds, hedge funds, and investment advisors), log market equity, log book equity, book/market, asset growth (investment), profitability to book equity, and pre-ranking CAPM beta for the 5 portfolios formed on quintiles of the intermediation measure $\epsilon_{i,t}$. Details on the construction of $\epsilon_{i,t}$ are presented in section 4.1. Sample spans 1980q2 to 2017q3.

Table 3: **Return Summary Stats For Portfolios Formed on Quintiles of Intermediation Measure** $\epsilon_{i,t}$

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
μ(Ex Ret)	8.76	10.14	10.46	11.2	10.63	1.79
t-stat	2.84	3.38	3.3	3.51	3.16	1.85
σ(Ex Ret)	38.97	37.05	39.33	40.02	42.33	12.22
Sharpe Ratio	.22	.27	.27	.28	.25	.15

This table reports the means, standard deviations, and Sharpe Ratios for the percent annualized excess returns for portfolios formed on quintiles of intermediation measure $\epsilon_{i,t}$. Details on the construction of $\epsilon_{i,t}$ are presented in section 4.1. Sample spans 1980q2 to 2017q3.

Table 4: **Regressions of Quintile-Sorted Portfolios Formed by Intermediation Measure $\epsilon_{i,t}$ on Contemporaneous Intermediary Shocks**

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Intermediary Shock	0.948	2.727**	3.570**	4.104**	5.082***	4.134***
	(0.75)	(2.24)	(2.58)	(2.31)	(3.45)	(4.21)
$\text{Mkt}^{NonFin} - \text{Rf}$	1.101***	1.028***	1.073***	1.068***	1.118***	0.017
	(21.59)	(20.96)	(18.28)	(14.55)	(19.56)	(0.41)
Observations	150	150	150	150	150	150
R^2	0.88	0.90	0.89	0.86	0.87	0.13

This table shows regressions of the intermediation measure $\epsilon_{i,t}$ portfolio quintile excess returns (and top minus bottom quintile spread) on risk factors as in (9) of the main text:

$$R^e_{i,t+1} = \alpha_i + \beta_{1,i}\text{Intermediary Shock}_{t+1} + \beta_{2,i}(\text{Mkt}^{NonFin}_{t+1} - R_{f,t}) + \nu_{i,t}$$

The first row of this table shows the coefficient estimates on the average of the standardized Federal Reserve primary dealer equity capital ratio shocks from He, Kelly, and Manela (2017) and the broker-dealer book leverage growth shocks from Adrian, Etula, and Muir (2014) for five portfolios formed on the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail), as well as the coefficient on the intermediary shocks for the top minus bottom quintile spread. The second row shows the betas on a version of the value-weighted market risk factor that excludes returns on financial stocks (SIC code between 6000 and 6999). The sample is quarterly and comprises 1980q2 to 2017q3. Newey-West t-stats are in parentheses. Quarterly excess returns are in annualized percent form and the intermediary shock is standardized. Sample spans 1980q2 to 2017q3.

Table 5: **Predictability Regressions of High minus Low Intermediation Spread Portfolio Returns On Intermediary Risk Bearing Capacity**

	(1)	(2)	(3)	(4)	(5)	(6)
η	2.828***	5.506***	2.806***	2.826***	2.818***	6.236***
	(2.87)	(3.57)	(2.83)	(2.84)	(2.87)	(3.93)
P/E		3.479				4.460*
		(1.53)				(1.90)
cay			0.401			0.658
			(0.49)			(0.77)
10Y-3Mo				-0.075		0.735
				(-0.07)		(0.80)
sentiment					1.418	1.726
					(1.37)	(1.56)
Observations	450	450	450	450	450	450
R^2	0.041	0.066	0.042	0.041	0.051	0.087

This table shows coefficients obtained from regressing overlapping quarterly returns at the monthly frequency of the high minus low intermediation portfolio excess returns on η, the average of the standardized primary dealer squared leverage from He, Kelly, and Manela (2017) and the negative of standardized broker dealer leverage from Adrian, Etula, and Muir (2014):

$$R^{Q5}_{t\to t+3} - R^{Q1}_{t\to t+3} = \alpha + \beta_1 \eta_t + \beta_2 Z_t + \nu_t$$

Controls include P/E, the cyclically-adjusted price to earnings ratio; cay, the consumption-wealth ratio from Lettau and Ludvigson (2001); the 10 year minus 3 month treasury term spread; and, the Baker and Wurgler (2006) sentiment index. Newey-West t-stats with four lags are presented in parentheses. All independent variables are standardized and excess returns are expressed in annualized percentage form. The high and low portfolios are formed on the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail). Sample spans 1980m4 to 2017m9.

Table 6: **Predictability Regressions of High minus Low Intermediation Spread Portfolio Returns On HKM and AEM State Variables**

	(1)	(2)	(3)	(4)	(5)	(6)
PD Lev. Sq.	2.023**	4.563***	2.035**	2.025**	2.133**	5.589***
	(2.22)	(3.52)	(2.22)	(2.23)	(2.41)	(3.98)
BD Lev.	-1.628*	-2.999***	-1.586*	-1.623*	-1.505	-3.273***
	(-1.79)	(-2.83)	(-1.72)	(-1.77)	(-1.63)	(-3.10)
P/E		3.938*				5.295**
		(1.67)				(2.13)
cay			0.425			0.878
			(0.52)			(1.04)
10Y-3Mo				-0.089		0.784
				(-0.08)		(0.86)
sentiment					1.458	1.895*
					(1.40)	(1.65)
Observations	450	450	450	450	450	450
R^2	0.041	0.070	0.042	0.041	0.052	0.096

This table shows coefficients obtained from regressing overlapping quarterly returns at the monthly frequency of the high minus low intermediation portfolio excess returns on the primary dealer squared leverage from He, Kelly, and Manela (2017) and the broker dealer leverage from Adrian, Etula, and Muir (2014):

$$R^{Q5}_{t\to t+3} - R^{Q1}_{t\to t+3} = \alpha + \beta_1 \text{PD Lev Sq}_t + \beta_2 \text{BD Lev}_t + \beta_3 Z_t + \nu_t$$

Controls include P/E, the cyclically-adjusted price to earnings ratio; cay, the consumption-wealth ratio from Lettau and Ludvigson (2001); the 10 year minus 3 month treasury term spread; and, the Baker and Wurgler (2006) sentiment index. All independent variables are standardized and excess returns are expressed in annualized percentage form. The high and low portfolios are formed on the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail). Sample spans 1980m4 to 2017m9.

Table 7: **Predictability Regressions of High minus Low Intermediation Spread Portfolio Returns On Financial Sector Stock Market Wealth Share**

	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Share	-2.577***	-4.038**	-2.571***	-2.575***	-2.379***	-3.876**
	(-3.06)	(-2.22)	(-2.88)	(-3.05)	(-2.75)	(-2.14)
P/E		2.087				2.092
		(0.88)				(0.89)
cay			0.032			-0.034
			(0.04)			(-0.04)
10Y-3Mo				-0.086		0.322
				(-0.08)		(0.34)
sentiment					0.928	0.854
					(0.88)	(0.78)
Observations	450	450	450	450	450	450
R^2	0.034	0.045	0.034	0.034	0.038	0.049

This table shows coefficients obtained from regressing overlapping quarterly returns at the monthly frequency of the high minus low intermediation portfolio excess returns on the share of stock market wealth held in the financial sector (SIC codes between 6000 and 6999):

$$R^{Q5}_{t\to t+3} - R^{Q1}_{t\to t+3} = \alpha + \beta_1 \text{Fin. Share}_t + \beta_3 Z_t + \nu_t$$

Controls include P/E, the cyclically-adjusted price to earnings ratio; cay, the consumption-wealth ratio from Lettau and Ludvigson (2001); the 10 year minus 3 month treasury term spread; and, the Baker and Wurgler (2006) sentiment index. Newey-West t-stats with four lags are presented in parentheses. All independent variables are standardized and excess returns are expressed in annualized percentage form. The high and low portfolios are formed on the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail). Sample spans 1980q2 to 2017q3.

Table 8: **Panel Regressions of Stock Excess Returns on Contemporaneous Intermediary Shocks Interacted With Intermediation Measure $\epsilon_{i,t}$**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intermediary Shock $\times$ $\epsilon_{i,t}$	9.01***			8.11***			10.0***		
	(5.32)			(4.96)			(4.63)		
Capital Shock $\times$ $\epsilon_{i,t}$		0.17***			0.18***			0.23***	
		(3.51)			(2.65)			(3.96)	
Leverage Shock $\times$ $\epsilon_{i,t}$		0.048*			0.048*			0.062*	
		(1.70)			(1.66)			(1.86)	
Ex Ret (Fin.) $\times$ $\epsilon_{i,t}$			0.19***			0.22**			0.31***
			(3.17)			(2.48)			(2.94)
$\text{Mkt}^{NonFin} - \text{Rf} \times \epsilon_{i,t}$				0.058	-0.010	-0.049	0.085	-0.014	-0.10
				(0.66)	(-0.09)	(-0.39)	(0.97)	(-0.15)	(-0.76)
SMB $\times$ $\epsilon_{i,t}$							0.064	0.056	0.075
							(0.38)	(0.33)	(0.47)
HML $\times$ $\epsilon_{i,t}$							-0.17	-0.21	-0.14
							(-1.16)	(-1.45)	(-0.78)
CMA $\times$ $\epsilon_{i,t}$							-0.099	-0.082	-0.21
							(-0.60)	(-0.51)	(-1.26)
RMW $\times$ $\epsilon_{i,t}$							0.39***	0.40***	0.36***
							(2.87)	(2.92)	(2.64)
UMD $\times$ $\epsilon_{i,t}$							-0.056	-0.032	-0.033
							(-0.60)	(-0.34)	(-0.37)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	211255	211255	211255	211255	211255	211255	211255	211255	211255
R^2	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24

This table shows estimates from panel regressions as in (13) of the main text:

$$R_{i,t+1} - R_{f,t} = \alpha_0 + \beta_1 F_{t+1} \times \epsilon_{i,t} + \beta_2 W_{t+1} \times \epsilon_{i,t} + \alpha_t + \alpha_i + \nu_{i,t+1}$$

Here F_{t+1} denotes shocks to intermediaries and W_{t+1} controls for other common shocks. The capital shocks refer to the Federal Reserve primary dealer equity capital ratio shocks proposed in He, Kelly, and Manela (2017), while the leverage shocks refer to the broker-dealer leverage shocks from Adrian, Etula and Muir (2014). Intermediary shock refers to the average of the standardized leverage and capital shocks. Financial sector return is the value-weighted return on the financial sector (stocks with SIC code between 6000 and 6999). Regressions control for a version of the value-weighted market risk factor that excludes financial stocks. Controls SMB, HML, CMA, RMW, UMD refer to the Fama-French (2015) risk factors and the up minus down momentum factor. In parentheses are t-stats that are clustered by time to adjust for cross-sectional correlation in the residuals and are also adjusted for one lag of autocorrelation. The Intermediary Shock measure is standardized and returns are in annualized percent form. Sample spans 1980q2 to 2017q3.

Table 9: **Predictive Panel Regressions of Stock Excess Returns on Intermediary State Variables Interacted With Intermediation Measure $\epsilon_{i,t}$**

	(1)	(2)	(3)	(4)	(5)	(6)
$\eta \times \epsilon_{i,t}$	12.3***			11.0***		
	(3.98)			(2.96)		
PD Lev. Squared $\times \epsilon_{i,t}$		7.01***			4.82**	
		(3.04)			(2.30)	
BD Lev. $\times \epsilon_{i,t}$		-8.38***			-8.00***	
		(-2.96)			(-2.70)	
Fin. Share $\times \epsilon_{i,t}$			-8.17***			-5.32*
			(-2.75)			(-1.86)
P/E $\times \epsilon_{i,t}$				-3.22	-4.29	-7.15**
				(-0.83)	(-1.15)	(-2.17)
cay $\times \epsilon_{i,t}$				1.24	1.33	0.54
				(0.53)	(0.56)	(0.22)
10Y-3Mo $\times \epsilon_{i,t}$				-0.0083	-0.0074	-0.0077
				(-0.37)	(-0.34)	(-0.34)
sentiment $\times \epsilon_{i,t}$				2.73	2.56	0.44
				(0.63)	(0.60)	(0.11)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	211255	211255	211255	211255	211255	211255
R^2	0.24	0.24	0.24	0.24	0.24	0.24

This table shows estimates from running predictive regressions of quarterly $t+1$ stock excess returns on date t state variables interacted with the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail). The state variable η is the average of the standardized primary dealer squared leverage ratio from He, Kelly, and Manela (2017) and the negative of the standardized broker-dealer leverage ratio from Adrian, Etula, and Muir (2014). Fin. Share is the share of stock market wealth held in financial stocks. The Controls include P/E, the cyclically adjusted P/E ratio; cay, the consumption-wealth ratio from Lettau, and Ludvigson (2001); the 10 year minus 3 month treasury term spread; and, the Baker and Wurgler (2006) sentiment index. All independent variables are standardized and returns are in annualized percent form. Sample spans 1980q2 to 2017q3.

Table 10: **Panel Regressions of Rolling Stock-Level Intermediary Risk Bearing Capacity Betas on Intermediation Measure** $\epsilon_{i,t}$

	Intermediary Shock	Capital Shock	Leverage Shock	Ex Ret (Fin.)
$\epsilon_{i,t}$	6.70***	0.14***	0.070***	0.17***
	(3.75)	(3.85)	(2.67)	(3.22)
Stock Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	188453	188453	188453	188453
R^2	0.53	0.54	0.50	0.55

This table shows regressions of rolling individual stock betas on the intermediation measure $\epsilon_{i,t}$ (which is constructed so as to be uncorrelated with fundamental stock characteristics; section 4.1 discusses this in more detail). Stock betas are obtained from regressions of the form

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \mathrm{F}_t + \beta_i^M \left(\mathrm{Mkt}_t^{NonFin} - \mathrm{Rf}_t\right) + \delta_{i,t}$$

using a window of plus or minus 15 quarters. Stocks betas must have been estimated using at least 20 observations to be included in the sample. Reported coefficients are then estimated from panel regressions taking the form

$$\widehat{\beta}_{i,t-15\to t+15} = \alpha_0 + \beta_1 \epsilon_{i,t} + \beta_2 Z_{i,t} + \alpha_t + \alpha_i + \nu_{i,t}$$

Controls $Z_{i,t}$ include gross profitability, investment (asset growth), CAPM beta, book/market, second-degree polynomial in log market cap and log book equity, plus stock and time fixed effects. In parentheses are t-statistics double clustered by stock and quarter. Returns and risk factors are expressed in annualized percentage terms, with the exception of the intermediary shock, which is standardized to zero mean and unit variance. Sample spans 1980q2 to 2017q3.

Table 11: **Robustness: Contemporaneous Portfolio Regressions**

	Original		Add WRDS Ratios		Just log(BE)		Value-Weighted		Drop Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intermediary Shock	4.13***	4.43***	3.42***	3.34***	2.76**	4.38***	6.13***	7.23***	4.07**	3.27*
	(4.21)	(3.05)	(3.46)	(2.83)	(2.60)	(3.17)	(5.20)	(5.33)	(2.53)	(1.75)
$\text{Mkt}^{NonFin} - \text{Rf}$	0.017	0.046	-0.025	0.036	0.19***	0.14**	-0.11	-0.14*	0.016	0.070
	(0.41)	(0.86)	(-0.58)	(0.73)	(4.09)	(2.50)	(-1.47)	(-1.84)	(0.32)	(1.09)
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	150	150	150	150	150	150	150	150	144	144
R^2	0.13	0.20	0.072	0.15	0.27	0.40	0.092	0.19	0.077	0.16

This table contains predictability regressions of high minus low excess returns for portfolios formed on the top and bottom quintiles of intermediation measure $\epsilon_{i,t}$ on risk factors

$$R^{Q5}_{i,t+1} - R^{Q1}_{i,t+1} = \alpha + \beta_1 \text{Intermediary Shock}_{t+1} + \beta_2(\text{Mkt}^{NonFin}_{t+1} - R_{f,t}) + \nu_t$$

The first two columns estimate the residual intermediation $\epsilon_{i,t}$ as done throughout the main text (and decribed in section 4.1); the next two add 40 financial ratios obtained from WRDS to the cross-sectional regression (8) from the main text; columns (5) and (6) include just a second degree polynomial in log book equity to estimate $\epsilon_{i,t}$. Columns (7)/(8) and (9)/(10) are, respectively, for value-weighted instead of equal-weighted portfolios and for a subsample that excludes the financial crisis (2008q1 through 2009q2). Odd columns control just for a version of the value-weighted market factor that excludes returns on financial stocks and even columns add the Fama-French (2015) non-market risk factors plus the momentum factor. The Intermediary Shock measure is formed as an average of the standardized shocks to primary dealer equity capital from He, Kelly, and Manela (2017) and broker-dealer leverage from Adrian, Etula, and Muir (2014). The Intermediary Shock measure is standardized and returns are expressed in annualized percent form. Newey-West t-stats are in parentheses. Sample spans 1980q2 to 2017q3.

Table 12: **Robustness: Predictive Portfolio Regressions**

	Original	Add WRDS Ratios	Just log(BE)	Value-Weighted	Drop Crisis
η	6.236***	5.535***	7.865***	5.604**	6.961***
	(3.93)	(3.57)	(4.62)	(2.56)	(3.10)
P/E	4.460*	3.753	5.810***	3.110	5.079*
	(1.90)	(1.58)	(2.91)	(1.04)	(1.79)
cay	0.658	0.862	1.700	-0.036	0.647
	(0.77)	(1.07)	(1.45)	(-0.03)	(0.74)
10Y-3Mo	0.735	0.304	1.513	1.415	0.737
	(0.80)	(0.47)	(1.36)	(0.98)	(0.78)
sentiment	1.726	1.479	0.394	3.655**	1.919*
	(1.56)	(1.40)	(0.33)	(2.50)	(1.67)
Observations	450	450	450	450	432
R^2	0.087	0.096	0.083	0.069	0.075

This table shows predictability regressions of high minus low excess returns for portfolios formed on the top and bottom quintiles of intermediation measure $\epsilon_{i,t}$ on on η, the average of the standardized primary dealer squared leverage from He, Kelly, and Manela (2017) and the negative of standardized broker dealer leverage from Adrian, Etula, and Muir (2014):

$$R^{Q5}_{t\to t+3} - R^{Q1}_{t\to t+3} = \alpha + \beta_1 \eta_t + \beta_2 Z_t + \nu_t$$

Regressions are for overlapping quarterly returns at the monthly frequency. The first column contains the original version for backing out residual intermediation $\epsilon_{i,t}$ (as used throughout the main text and described in 4.1), while the second column estimates the residual intermediation $\epsilon_{i,t}$ by adding 40 financial ratios obtained from WRDS to the cross-sectional regression (8) using to obtain $\epsilon_{i,t}$; the third column includes just a second degree polynomial in log book equity to estimate $\epsilon_{i,t}$. The last two columns are, respectively, for value-weighted instead of equal-weighted portfolios and for a subsample that excludes the financial crisis (2008m1 through 2009m6). Newey-West t-stats with four lags are in parentheses. All independent variables are standardized and returns are in annualized percent form. Sample spans 1980m4 to 2017m9.

Appendices

A Characteristics-Based Framework For Empirical Tests

I present here a simple setting (which borrows heavily but is slightly different from the characteristics-based demand setup of Koijen and Yogo, 2019) that leads to the empirical specification for backing out the residual intermediation measure $\epsilon_{i,t}$ that I use to form portfolios. As in the model from section 2, assume there are two investors, a representative institutional investor and a representative household with constant-absolute risk aversion utility and respective risk tolerance ρ_I and ρ_H (where for now I have suppressed any dependence of risk tolerances on underlying state variables). Assume that there are N assets in net supply 1 whose cashflows are distributed multivariate normal, $D \sim N(\mu, \Sigma)$. Similarly to Koijen and Yogo (2019), I assume that Σ can be decomposed as $\Sigma = \beta\beta' + \sigma^2 I$, where β contains asset factor loadings, σ^2 is idiosyncratic variance, and β is of dimension $N \times 1$. There is also a risk-free asset whose gross return R_f is fixed exogenously. Let X be a $N \times k$ matrix of stock characteristics. I assume that the representative household and institutional investor agree that

$$\beta = X\Pi + \pi$$

where Π is a $k \times 1$ vector and π is a constant $N \times 1$ vector. Hence fundamental loadings β are affine in characteristics.[22]

Now, assume that μ is linear in characteristics, but households and institutional investors may disagree on the mapping from characteristics to μ in the following manner. Households mistakenly believe that the mean μ follows

$$\mu_H = X\Phi_H + \phi_H + \epsilon_H$$

while institutional investors' (correct) estimate of the mean μ is given by

$$\mu_I = X\Phi_I + \phi_I \tag{16}$$

Here ϕ_H and ϕ_I are constant across assets and ϵ_H may differ across assets. The residual ϵ_H is the component of household's beliefs about the mean of the asset payoff distribution that are uncorrelated with the asset characteristics.

[22]Since any multifactor model of payoffs/returns implies a single factor model where the stochastic-discount factor is the lone factor, this essentially assumes that loadings on the SDF are affine in characteristics.

Given constant absolute risk aversion utility, the optimal demand for agent j is

$$\theta_j = \rho_j \Sigma^{-1}(\mu_j - R_f P)$$

Imposing market clearing ($\theta_I + \theta_H = 1$) gives the following expression for prices:

$$P = \frac{\rho_I \mu_I + \rho_H \mu_H - \Sigma \mathbf{1}}{R_f(\rho_I + \rho_H)} \tag{17}$$

Substituting out price using market clearing gives the following for intermediary demand (or percent intermediated):

$$\begin{aligned}
\theta_I &= \rho_I \Sigma^{-1} \left[\frac{\rho_H(\mu_I - \mu_H) + \Sigma \mathbf{1}}{\rho_I + \rho_H} \right] \\
&= \alpha \left(\beta\beta' + \sigma^2 I \right)^{-1} (X\Delta\Phi + \Delta\phi - \epsilon_H) + \delta \mathbf{1} \\
&= \frac{\alpha}{\sigma^2} \left(I + \frac{1}{\kappa} \beta\beta' \right) (X\Delta\Phi + \Delta\phi - \epsilon_H) + \delta \mathbf{1} \\
&= \frac{\alpha}{\sigma^2} \left(X\Delta\Phi + \Delta\phi - \epsilon_H + (X\Pi + \pi)\eta \right) + \delta \mathbf{1} \\
&= \frac{\alpha}{\sigma^2}(\Delta\phi + \pi\eta) + \delta \mathbf{1} + X\frac{\alpha}{\sigma^2} (\Delta\Phi + \Pi\eta) - \frac{\alpha}{\sigma^2}\epsilon_H \\
&\equiv a + XB + \tilde{\epsilon}
\end{aligned} \tag{18}$$

Where the terms in the above are defined as follows:

$$\alpha = \frac{\rho_I \rho_H}{\rho_I + \rho_H}, \ \delta = \frac{\rho_I}{\rho_I + \rho_H}, \ \kappa = -(\sigma^2 + \beta'\beta),$$

$$\Delta\Phi = \Phi_I - \Phi_H, \ \Delta\phi = \phi_I - \phi_H, \ \eta = \frac{1}{\kappa}\beta'(X\Delta\Phi + \Delta\phi - \epsilon_H),$$

$$B = \frac{\alpha}{\sigma^2}(\Pi\eta + \Delta\Phi), \ a = \frac{\alpha}{\sigma^2}(\Delta\phi + \pi\eta) + \delta\mathbf{1}, \text{ and } \tilde{\epsilon} = -\frac{\alpha}{\sigma^2}\epsilon_H$$

The relation between the second and third lines follows from the Woodbury matrix identity and then simplifying. Note that the constant η is obtained by multiplying β by X and ϵ_H, the current characteristics of all assets and the residual component of the household's estimate of the mean for all assets. The constants α and δ also depend on the current risk tolerance of the agents in the model. Hence the parameters in (18) can only be identifed with time-specific coefficients, which implies a cross-sectional regression as in (8) in the main text:

$$\text{Percent Intermediated}_{i,t} = \alpha_t + \beta_t X_{i,t} + \epsilon_{i,t}$$

I now show that under the assumptions above the residual $\epsilon_{i,t}$ recovers a component of intermediary demand along which the price response to intermediary risk tolerance shocks is strictly increasing. Returning to the equation for prices:

$$P = \frac{\rho_I \mu_I + \rho_H \mu_H - \Sigma \mathbf{1}}{R_f(\rho_I + \rho_H)}$$

$$= \frac{\rho_I(\omega)(X\Phi_I + \phi_I) + \rho_H(\zeta)(X\Phi_H + \phi_H + \epsilon_H) - \Sigma \mathbf{1}}{R_f(\rho_I(\omega) + \rho_H(\zeta))}$$

Now, letting ρ_I depend on the state variable ω and ρ_H on the state variable ζ as before, we can take the total derivative of price with respect to a local shock to these variables:

$$dP = \frac{\rho_I^{'}(\omega)\left(\rho_H(\zeta)(\Delta\Phi X + \Delta\phi - \epsilon_H) + \Sigma \mathbf{1}\right)}{R_f(\rho_I(\omega) + \rho_H(\zeta))^2} d\omega$$

$$- \frac{\rho_H^{'}(\zeta)\left(\rho_I(\omega)(\Delta\Phi X + \Delta\phi - \epsilon_H) + \Sigma \mathbf{1}\right)}{R_f(\rho_I(\omega) + \rho_H(\zeta))^2} d\zeta$$

$$\equiv \beta_\omega d\omega + \beta_\zeta d\zeta$$

Note that since we assume $\rho_I^{'}(\omega) > 0$, β_ω is strictly decreasing in ϵ_H, or equivalently is strictly increasing in $\tilde{\epsilon} = -\frac{\alpha}{\sigma^2}\epsilon_H$. Since the residuals $\epsilon_{i,t}$ in the regression equation (8) are analogous to $\tilde{\epsilon}$ in this setup, this implies that sorting on $\epsilon_{i,t}$ should induce variation in betas on proxies for shocks to intermediary risk tolerance. Note also that in the case where $\Phi_I = \Phi_H$ and $\phi_I = \phi_H$, so that $\Delta\Phi = 0$ and $\Delta\phi = 0$, we recover the expressions in section 2 by defining $\epsilon_H = \lambda$.

This setting also recovers the differential return predictability for high ϵ_H assets as in proposition 2. Define the risk premium on asset j by $E[R_{p,j}] = \mu_j - R_f P_j$, and suppose $X_2 = X_1$, so that asset characteristics are the same, but $\epsilon_{H,1} < \epsilon_{H,2}$ (or equivalently, $\tilde{\epsilon}_1 > \tilde{\epsilon}_2$, so that asset 1 is more intermediated) . Then

$$E[R_{p,1} - R_{p,2}] = \frac{\rho_H(\zeta)(\epsilon_{H,2} - \epsilon_{H,1}))}{R_f(\rho_I(\omega) + \rho_H(\zeta))}$$

which is positive and strictly decreasing in ω. Hence $\partial E[R_{p,1} - R_{p,2}]/\partial\omega < 0$ and the difference in expected returns for high minus low intermediated assets decreases (increases) when intermediaries are more (less) risk tolerant, as in proposition 2, implying that empirical proxies for current intermediary risk tolerance should negatively predict the return spread for high minus low $\epsilon_{i,t}$ assets.

B Model Extension

Consider the following extension on the model from section 2–suppose that household risk tolerance ρ_H is a function of both the state variable ζ, which does not move intermediary risk tolerance, and ω, which does induce changes in intermediary risk tolerance. Then for local changes in ω and ζ

$$\mathrm{d}P = \frac{\rho_I^{'}(\omega)(\Sigma\mathbf{1} - \lambda\rho_H(\zeta)) + \rho_{H_\omega}(\zeta,\omega)(\Sigma\mathbf{1} + \lambda\rho_I(\omega))}{R_f(\rho_I(\omega) + \rho_H(\zeta,\omega))^2}\mathrm{d}\omega + \frac{\rho_{H_\zeta}(\zeta,\omega)(\Sigma\mathbf{1} + \lambda\rho_I(\omega))}{R_f(\rho_I(\omega) + \rho_H(\zeta,\omega))^2}\mathrm{d}\zeta \tag{19}$$

Proposition 3 follows easily from here. As proposition 3 assumes the partial derivative $\rho_{H_\omega}(\zeta,\omega) > 0$, then since $\rho_I^{'}(\omega)$ is multiplied by λ with negative sign and $\rho_{H_\omega}(\zeta,\omega)$ is multiplied by λ with positive sign, the two effects work in opposite direction for the coefficient on $d\omega$. Moreover, as percent intermediated is strictly decreasing in λ, the negative sign on $\rho_I^{'}(\omega)$ causes betas on shocks to ω to increase with intermediation, while $\rho_{H_\omega}(\zeta,\omega)$ does the opposite. Therefore if betas increase with intermediation (holding all else constant), it must be because of price responses to changes in intermediary risk tolerance.

It should be noted that this doesn't have to be the case if $\rho_{H_\omega}(\zeta,\omega) < 0$; however, it seems less likely in practice that shocks to household and intermediary risk tolerance are negatively correlated. Indeed Haddad and Muir (2018) argue that if anything $\rho_{H_\omega}(\zeta,\omega) \geq 0$, as episodes where intermediaries become more risk averse are also likely to be periods of time where household risk aversion increases (the financial crisis of 2008-2009 being a particularly salient example).

C Data Appendix

C.1 Construction of AEM Leverage Factor

As noted by Cho (2019), changes to the Federal Reserve Flow of Funds data have significantly altered the implied broker-dealer leverage ratio. Starting with the first quarter of 2014, repo assets (reverse repo) are included in assets and just repo liabilities, rather than net repo, are included in the liabilities section. In order to make my leverage factor consistent with the construction in the original Adrian, Etula, and Muir (2014) paper, I obtain the broker-dealer leverage from Table L128 of the 2013q4 Flow of Funds release. I then compute the leverage as

$$\text{Leverage}_t = \frac{\text{Total Financial Assets}_t}{\text{Total Financial Assets}_t - \text{Total Financial Liabilities}_t} \tag{20}$$

I then seasonally adjust as described in Adrian, Etula, and Muir (2014). Cho (2019) suggests that the following change allows one to extend the original AEM factor

$$\text{Leverage}_t = \frac{\text{Total Financial Assets}_t - \text{Repo Assets}_t}{\text{Total Financial Assets}_t - \text{Total Financial Liabilities}_t - \text{FDI in US}_t} \tag{21}$$

This accounts for changes to foreign direct investment reflected in liabilities in later releases of the Flow of Funds. However, I find that when I use the above for the most recent releases, the two methods (20) and (21) agree until the end of 2010 at which point broker dealer leverage begins an upward spike for (21) relative to (20), which spike becomes extreme to the point that leverage becomes negative towards the end of the sample. Due to this issue, I simply use (20) through the 2013q4 release and then extend the series using (20) with updated Flow of Funds data, which is also consistent with the extended leverage factor data posted on Tyler Muir's website. I further seasonally adjust the leverage growth series using expanding window regressions of leverage growth on quarterly dummies as in AEM to arrive at my final leverage factor.

C.2 Selection of WRDS Ratios For Final Sample

For my robustness checks in section 4.4 I obtain the 73 financial ratios from the Wharton Research Data Services Financial Ratios suite. I find that data availability are sparse, so I do the following:

1. When firm dividend yield and dividend/price ratios are missing, I assume they are equal to zero
2. I replace missing values for any variables with their lags as of up to 8 quarters previous
3. I then check the fraction of missing observations for stocks that overlap with my main sample. If this fraction is greater than 1% I exclude the ratio from the analysis.

This leaves the following ratios:
Enterprise Value Multiple, Price/Sales, Price/Cash flow, Dividend Payout Ratio, Net Profit Margin, Operating Profit Margin Before Depreciation, Operating Profit Margin After Depreciation, Gross Profit Margin, Pre-tax Profit Margin, Cash Flow Margin, Return on Assets, Return on Equity, Return on Capital Employed, After-tax Return on Average Common Equity, After-tax Return on Invested Capital, After-tax Return on Total Stockholders Equity, Gross Profit/Total Assets, Common Equity/Invested Capital, Long-term Debt/Invested Capital, Total Debt/Invested Capital, Capitalization Ratio, Cash Balance/Total Liabilities, Total Debt/Total Assets, Total Debt/EBITDA, Long-term Debt/Total Liabilities,

Cash Flow/Total Debt, Total Liabilities/Total Tangible Assets, Long-term Debt/Book Equity, Total Debt/Total Assets, Total Debt/Capital, Total Debt/Equity, Asset Turnover, Sales/Invested Capital, Sales/Stockholders Equity, Research and Development/Sales, Advertising Expenses/Sales, Labor Expenses/Sales, Accruals/Average Assets, Price/Book, and Dividend Yield.

Though the WRDS book/market ratio satisfies sampling criteria, I also exclude this variable because I already include a version of book/market in the regression. Finally, these variables are winsorized cross sectionally at the 1% level to deal with outliers.