Do Intermediaries Matter for Aggregate Asset Prices?

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ABSTRACT

Poor financial health of intermediaries coincides with low asset prices and high risk premiums. Is this because intermediaries matter for asset prices, or because their health correlates with economy-wide risk aversion? In the first case, return predictability should be more pronounced for asset classes in which households are less active. We provide evidence supporting this prediction, suggesting that a quantitatively sizable fraction of risk premium variation in several large asset classes such as credit or MBS is due to intermediaries. Movements in economy-wide risk aversion create the opposite pattern, and we find this channel also matters.

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Poor financial health of financial intermediaries such as investment banks, commercial banks, or hedge funds tends to coincide with low aggregate asset prices and high risk premia.[1] This correlation suggests that the health of the financial sector matters for aggregate asset prices.[2] However, this evidence alone does not rule out the possibility that intermediaries reflect or are correlated with other frictionless factors driving asset prices. For example, consider the 2008 financial crisis, during which risk premia rose substantially. While there was indeed a decline in intermediary risk-bearing capacity, household risk aversion likely also rose, in which case the extent to which the fall in intermediation mattered for aggregate asset prices is unclear.[3] In this paper we examine how much variation in aggregate risk premia can be ascribed to intermediaries versus households.

To address this question, we compare variation in risk premia across more and less intermediated asset classes. We start by regressing the return of each asset class on a proxy for the effective risk-bearing capacity of intermediaries. Specifically, we estimate

$$r_{i,t+1} = a_i + b_i \gamma_{I,t} + \varepsilon_{i,t+1}, \quad i = 1, ..., N, \quad t = 1, ..., T, \tag{1}$$

where $\gamma_{I,t}$ is an empirical proxy for intermediaries' effective risk aversion

[1] See, for examples, Adrian, Etula, and Muir (2014), Hu, Pan, and Wang (2013), Haddad and Sraer (2020), Muir (2017), and He, Kelly, and Manela (2017).

[2] He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) provide models of how the financial sector impacts asset prices.

[3] Santos and Veronesi (2020) discuss a frictionless model that generates some of the empirical patterns associated with intermediation, leverage, and asset prices.

— the negative of intermediaries' risk-bearing capacity — and $r_{i,t+1}$ is the excess return on asset class i. We then compare the degree of predictability across these asset classes, captured by the regression R^2, the percentage change in risk premium relative to its mean ($b_i/\mathbb{E}[r_i]$), or the change in risk premium relative to the volatility of the asset class ($b_i/\sigma(r_i)$). We find relatively more predictability for asset classes that are more intermediated (e.g., mortgage-backed securities, credit default swaps, currencies, commodities) and relatively less predictability for asset classes that are less intermediated (e.g., stocks). We argue that these differences in the predictability of more versus less intermediated asset classes provide a lower bound for how much intermediaries matter in each asset class.

We clarify our argument in a simple model. When either intermediaries or households are less willing to bear risk, risk premia increase. Because variables that proxy for intermediary risk aversion are likely positively correlated with household or economy-wide risk aversion, evidence of a predictive relation alone (positive b_i) does not uncover how much variation in risk premia we can ascribe to intermediaries. Comparing across asset classes with different ease of access to households overcomes this challenge. To capture this distinction, we assume that households face costs to invest directly in some asset classes relative to investing indirectly through an intermediary.[4]

[4]Our model is related in spirit to He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) but includes many assets and does not assume that households are unable to invest directly in the assets (this is equivalent to an infinite cost in our setting). Related, Koijen and Yogo (2019) study how institutional demand affects individual stock prices, but their framework does not model the substitution of households' direct versus

For example, this cost is high for CDS and low for stocks. In asset classes with easy direct access, a drop in intermediary risk-bearing capacity does not have a large impact on premia since households can easily substitute or "step in" to these markets. With a high cost of direct investment, households cannot absorb the intermediary positions through direct holdings, so risk premia experience a large increase. The predictive relation will therefore be stronger in more intermediated asset classes. Changes in household risk aversion generate the opposite prediction, namely, a more substantial impact on less intermediated assets and a smaller impact on more intermediated assets.

To implement our test, we construct proxies for intermediary risk-bearing capacity ($\gamma_{I,t}$), asset class returns, and the degree to which intermediaries are active in each asset class. To measure risk-bearing capacity, we rely on existing literature on intermediary asset pricing, which provides foundations for how risk appetite should be measured empirically. Our main specification uses a standardized average of broker-dealer book leverage from Adrian, Etula, and Muir (2014) and the market equity of primary dealers from He, Kelly, and Manela (2017). We show robustness to alternative proxies for intermediary risk appetite as well. It is worth emphasizing that our exercise does not rely on exactly measuring intermediary risk appetite. We do not model the drivers of intermediary risk-bearing capacity in a micro-founded way as in He and Krishnamurthy (2013) or Adrian and Shin (2014) (i.e., we do not offer a theory of intermediary risk-bearing capacity).[5] We also

indirect holdings.

[5]See also Brunnermeier and Pedersen (2009), Danielsson, Shin, and Zigrand (2013),

acknowledge that variation in our proxy is unlikely to be "exogenous."[6] We overcome these identification challenges by studying a novel dimension of the aggregate data.

We employ the following asset classes, ranked from least to most intermediated: stocks, bonds, options, sovereign bonds, commodities, FX, MBS, and credit (i.e., CDS contracts).[7] To arrive at this ranking, we use the relative holdings of households and institutions, which are based on quantity and position data from Flow of Funds (FoF) and the Bank of International Settlements (BIS), asset class risk exposures, which are based on value-at-risk (VaR) measures taken from intermediary 10-K filings, and ETF expense ratios, which help us gauge households' cost of direct exposure to the asset classes. We also extend our analysis to an alternative set of return series. We compare the predictability of hedge fund returns for strategies of various complexity — convertible-bond arbitrage and fixed-income arbitrage at one extreme, and the overall stock market at the other.[8]

and Duffie (2010), among many others.

[6]In fact, in most theories the health of the financial sector is a state variable that responds endogenously to more fundamental shocks.

[7]Some of our assets are in zero net supply. This is fine as long as the asset return is positively correlated with risk that intermediaries are exposed to. For example, intermediaries on net will be positively exposed to credit risk and hence the CDS premium will reflect that credit risk is positive on net. This positive exposure is strongly supported empirically (He, Kelly, and Manela (2017)). We discuss the issue of asset supply further in Section III.

[8]Mitchell, Pedersen, and Pulvino (2007) and Hu, Pan, and Wang (2013) argue and show that intermediary capital matters for the returns of these strategies.

We compare the degree of predictability across asset classes. The raw predictive coefficient b_i is not an adequate metric, and we need to normalize returns into the same "units" to draw comparisons. To see why, suppose that one asset class is just a levered version of another. Then any variable that predicts returns in the original asset class will mechanically have a larger coefficient on the levered asset class. Dividing the regression coefficient by return volatility ($b_i/\sigma(r_i)$) addresses this effect. It also provides an intuitive interpretation of the coefficient as the degree of predictability relative to the asset's volatility (closely related to the R^2 in the predictive regression). Scaling by unconditional returns ($b_i/\mathbb{E}(r_i)$) also addresses this issue. Our model suggests that this second approach, that is, focusing on the *elasticity* of the risk premium to intermediary risk aversion, constitutes a better way to capture other dimensions of the differences across asset classes (e.g., differences in unconditional betas). While we prefer this normalization economically, there is an empirical trade-off because average returns are much harder to estimate than standard deviations. We therefore consider both scalings in our empirical analysis and consistently document stronger predictability for more intermediated asset classes. An important aspect of statistical inference in the case of elasticities is to account for uncertainty in mean returns estimates, which we divide by. We propose a Bayesian approach to do so and show that sharp statistical conclusions hold in this case under reasonable assumptions. One can impose that risk premiums on these broad asset classes are not negative, or can shrink estimates of mean returns toward the assumption of constant unconditional Sharpe ratios across asset classes. We provide economic and empirical arguments in favor of these assumptions.

Our main argument does not rely on any controls for household risk aversion, because we need do not need to take a firm stand on the behavior of this quantity. However, having a proxy for household risk aversion allows us to dig deeper and quantify the role of households for prices. In our framework, risk premia respond with an opposite pattern across asset classes to households' willingness to bear risk relative to intermediaries. We confirm this observation in the data, which strengthens our mechanism, by using the *cay* measure of Lettau and Ludvigson (2001) and the habit measure of Campbell and Cochrane (1999). In particular, we find substantially *less* predictability from these measures in more intermediated asset classes. This observation also confirms that our main result is not mechanical: not all return predictors exhibit an increasing pattern as one moves to more intermediated asset classes.

We combine these measured differences in predictability across asset classes to quantify bounds on the role of the two types of investors for risk premia. Our first set of results provides a lower bound on the extent to which intermediaries matter. Predictions with proxies for household risk-aversion give a lower bound for their role as well. We decompose the variation in the risk premium attributable to intermediaries versus households for each asset class. For example, we find that we can attribute about 60% of the variation in the risk premium on CDS to intermediaries. Similarly, we can attribute about 40% of the variation in the risk premium on stocks to households. A remaining fraction of the variation for each asset class we cannot assign to either intermediaries or households based on our lower bounds.

Finally, we discuss limitations of the assumptions behind our study and explore other possibilities that could explain our results. Most importantly, our framework thus far considers variation in the risk aversion of intermediaries and household. We allow for (i) arbitrary unobserved time-variation in effective risk aversion (i.e., we do not tie household risk aversion to a specific model but allow it to move freely), (ii) arbitrary unconditional covariances of asset classes with household marginal utility (that is, we do not take a stand on unconditional betas, nor do we tie them to covariance with observables like consumption growth), and (iii) arbitrary time-varying volatility of the household pricing kernel. However, other factors that drive risk premia may also change. For example, the covariance of asset payoffs might change and be correlated with the other variables. We show that our results are robust to including proxies for changing covariances in the predictive regressions (e.g., time-varying volatilities and betas) or to the possibility that intermediary risk aversion proxies for time-varying loadings on standard risk factors using the framework of Shanken (1990). Further, while we predict differential changes in risk premia across the asset classes, we do not predict differential changes in risk. More broadly, these time-varying covariances would also have to have a unique factor structure to line up perfectly with our results. In particular, it has to be case that risk increases more for intermediated asset classes when intermediary risk aversion rises. Across of variety of risk measures, we find no evidence of such a relationship.

Our findings are related to a broader literature studying the link between intermediary balance sheets and asset prices (Adrian, Etula, and Muir (2014); Hu, Pan, and Wang (2013), Haddad and Sraer (2020), He, Kelly, and Manela (2017)). Closely related to our work, He, Kelly, and Manela (2017) show that an intermediary factor helps explain the cross-section of returns for many asset classes. The main difference is that this literature typically studies intermediary Euler equations, which test for optimality of decisions that link intermediary marginal utility to asset returns but do not quantify whether intermediaries matter for risk premia. We illustrate this point in our model. Our paper also relates to more "micro" evidence, which provides sharp evidence that intermediaries matter for particular individual asset prices at particular points in time. Du, Tepper, and Verdelhan (2018) document stronger violations of covered interest parity at end-of-quarter financial reporting dates, when regulatory constraints are more binding. Some other examples include Siriwardane (2019), Fleckenstein, Longstaff, and Lustig (2014), Lewis, Longstaff, and Petrasek (2017), Krishnamurthy (2010), and Mitchell, Pedersen, and Pulvino (2007).[9] While these studies are important in documenting detailed price deviations related to intermediary risk-bearing capacity in specific periods, it is often unclear what these results imply for the broad behavior of aggregate asset prices.

The paper is organized as follows. Section I presents our framework and the model, Section II describes the data, and Section III presents the main empirical results. Section IV provides additional analysis, including results using hedge fund returns. Section V takes stock of our results in the context of the literature on intermediary asset pricing. Section VI concludes.

[9] Duffie (2010), Mitchell and Pulvino (2012), and He and Krishnamurthy (2018) offer thorough discussions of this literature.

I. Separating the Role of Intermediaries and Households for Asset Prices

In this section we introduce our test for the role of intermediaries for risk premia. We first present the basic ideas behind our empirical strategy. We then develop a more formal model. This simple theory guides our empirical implementation, but also helps us understand potential limitations to interpretation of existing evidence on intermediary asset pricing.

A. The Test

Economic Question. We are interested in whether the health of the financial sector affects conditional risk premia. The challenge in establishing this link is that intermediaries are not the only ones that can affect risk premia: households, through changes in how they perceive risk or their risk aversion, can also affect risk premia. This can be modeled as follows:

$$\tilde{r}_{i,t+1} = a_i + \beta_{i,H}\gamma_{H,t} + \beta_{i,I}\gamma_{I,t} + \varepsilon_{i,t+1}, \tag{2}$$

where i indexes assets and t time, and $\tilde{r}$ denotes the realized excess return on asset i divided on by an asset-specific normalization constant such as the sample average or standard deviation of excess returns.[10] Scaling returns before running the regression is identical to regressing unscaled returns and scaling the coefficient and makes results comparable across assets. The terms

[10]To see that this equation defines risk premia dynamics, take the conditional expectation: $\mathbb{E}_t\left[\tilde{r}_{i,t+1}\right] = a_i + \beta_{i,H}\gamma_{H,t} + \beta_{i,I}\gamma_{I,t}$.

$\gamma_{H,t}$ and $\gamma_{I,t}$ capture the effective risk aversion of households and of intermediaries, respectively, where we refer to anything that effects the willingness to bear risk — for intermediaries this could include losses in net worth, constraints on leverage, and so on (we return to these interpretations later) — as "effective risk aversion" and we refer to the negative of effective risk aversion as risk appetite. Naturally, one expects the coefficients $\beta_{i,H}$ and $\beta_{i,I}$ to be nonnegative. We want to determine whether $\beta_{i,I}$ is strictly positive and the magnitude of this effect.

Measurement Challenge. If one could perfectly measure the two risk appetites, this simple predictive regression would immediately provide estimates of these coefficients. However, in general this is not possible because risk appetite is imprecisely measured. What econometricians can observe are proxies for these variables, which we denote by $\hat{\gamma}_{I,t}$ and $\hat{\gamma}_{H,t}$. It is reasonable to assume that we have valid proxies, that is that these variables are positively correlated with their actual counterparts. However, because the risk appetites of households and intermediaries are likely positively correlated, it is natural to expect these proxies to also correlate positively with the risk appetite of the other group. In short, we have $\mathrm{cov}(\hat{\gamma}_{I,t}, \gamma_{I,t}) > 0$ and $\mathrm{cov}(\hat{\gamma}_{I,t}, \gamma_{H,t}) \geq 0$. An implication of these properties is that the reduced-form estimate $b_{i,I}$ in the regression

$$\tilde{r}_{i,t+1} = a_i + b_{i,I}\hat{\gamma}_{I,t} + \varepsilon_{i,t+1} \tag{3}$$

is positively influenced by both $\beta_{i,H}$ and $\beta_{i,I}$. In other words, measures of intermediary health can forecast returns because intermediaries' health affects expected returns ($\beta_{i,I} > 0$) or because intermediaries' health proxies for households' risk appetite and this appetite affects expected returns ($\beta_{i,H} > 0$). The example of the 2008 financial crisis is useful: while risk premia did spike substantially, and the financial sector was in poor shape, aggregate risk aversion increased in the same period and hence it is unclear whether the changes in risk premia were due to the collapse in intermediation or not.

Using the Cross-Section. A simple assumption allows us to overcome this challenge: the effects of intermediaries and households should vary in opposite directions *across* asset classes. This assumption is intuitively appealing. When an asset is more specialized or more difficult for households to access directly, households play a weaker role in its risk premium (low $\beta_{i,H}$) and intermediaries play a larger role (high $\beta_{i,I}$). The behavior of the estimate $b_{i,I}$ across asset classes combines these opposite patterns. Therefore, if $b_{i,I}$ increases as one moves to more intermediated asset classes, we can conclude that intermediaries affect prices. In addition, the strength of this relation offers a lower bound on intermediaries' importance. Indeed, if the proxy for intermediary risk appetite captures household risk aversion, this will lead to a smaller slope across asset classes than the actual effect of intermediaries. Internet Appendix Section I.A derives these conclusions formally.[11]

We next turn to a simple model that serves three purposes. First, it establishes a clear economic motivation for the structural relation of equation (2). Second, it justifies our assumption about the pattern of predictive

[11]The Internet Appendix is available in the online version of the article on the Journal of Finance website.

coefficients across asset classes. An important aspect of this comparison is how to appropriately make returns comparable across asset classes – the tilde in our return regressions. Third, it allows us to understand limitations to interpretation of existing evidence on intermediary asset pricing.

B. *An Asset Pricing Model with Intermediaries and Households*

B.1. Setup

There are two periods, 0 and 1, and a representative household. There is a risk-free saving technology with return one, and n risky assets with supply given by the vector S. Investment decisions are made at date 0 and payoffs are realized at date 1. The payoffs of the risky assets are jointly normally distributed, with mean μ and positive definite variance-covariance matrix Σ. The household has exponential utility with constant absolute risk aversion coefficient γ_H. We write p to denote the vector of equilibrium asset prices and assume that all decisions take prices as given.

The household can invest in the assets in two ways. First, the household can buy the assets directly, but at some cost. We assume that the household faces a quadratic cost per unit of risk parametrized by the diagonal nonnegative matrix C to invest in the various risky assets. This corresponds to a cost $\frac{1}{2}D'\Sigma_{diag}CD$ of investing in a vector D of the risky assets, with Σ_{diag} a matrix containing the diagonal elements of Σ. A simple motivation for this feature is that it is difficult for households to access some risky asset markets, for instance, complex financial products. Existing models of intermediation such as He and Krishnamurthy (2013) typically assume that households cannot invest in risky assets at all, $C = \infty$. In a slightly different specification, there is a discretely lower value to risky assets when in the hands of households; see, for instance, Brunnermeier and Sannikov (2014). Households might also be less able to manage portfolios of risky assets, making them more risky in effect, as in Eisfeldt, Lustig, and Zhang (2017). It might also be the case that households are only imperfectly informed about intermediaries' trades and therefore do not completely undo changes in their balance sheets through direct trading. More generally, households might have preferences for some asset classes over others for reasons beyond risk and reward. These interpretations highlight that the cost is a stand-in for willingness or ability to directly invest in an asset class.

Second, the household can invest through an intermediary that it owns. The intermediary can access markets at no cost and can pass through its payoffs to the household. However, the household cannot completely control the intermediary's investment decisions. We model this distinction by assuming that the intermediary invests as if it has exponential utility with risk-aversion parameter γ_I. We assume that $\gamma_I \geq \gamma_H$, that is, intermediaries are not willing to bear all of the risks that households want in the first place.[12] In practice, the risk-taking decisions of intermediaries may differ from those of households for many reasons. For instance, managers of financial institutions might have different preferences than their investors and limits to contracting

[12] This assumption is distinct from the assumption in many models that the *relative* risk aversion of intermediaries is lower than that of households. The two assumptions can coexist as long as the intermediary sector is not too large.

prevent going around this difference. This approach is pursued, for example, in He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) (see also He and Krishnamurthy (2018)). Financial institutions also face regulations explicitly limiting their risk-taking. For example, the Basel agreements specify limits on risk-weighted capital, measured by pre-specified risk weights or VaR. Adrian and Shin (2014) explore this channel.

The two assumptions above are voluntarily stylized, and we discuss them in more detail in Internet Appendix Section I.D. Figure 1 summarizes the setup.

[Insert Figure 1 about here.]

Because of exponential utility, initial endowments do not affect the demand for risky assets and thus we ignore them hereafter. The intermediary's problem determining its demand D_I for the risky assets is therefore

$$\max_{D_I} \; D_I' (\mu - p) - \frac{\gamma_I}{2} D_I' \Sigma D_I. \tag{4}$$

The household takes as given the investment decision of the intermediary when making her choice of direct holding D_H,

$$\max_{D_H} (D_H + D_I)' (\mu - p) - \frac{\gamma_H}{2} (D_H + D_I)' \Sigma (D_H + D_I) - \frac{1}{2} D_H' \Sigma_{diag} C D_H. \tag{5}$$

An equilibrium of the economy is a set of prices p and demands D_I^* and D_H^* such that the intermediary's and the household's decisions are optimal, and the risky asset market clears. The first two conditions imply that D_I^* and D_H^* solve problems (4) and (5), respectively. The market-clearing condition is given by

$$D_H + D_I = S. \tag{6}$$

B.2. Equilibrium Portfolios and Prices

We now characterize the equilibrium. The intermediary's demand follows the classic Markowitz result,

$$D_I^* = \frac{1}{\gamma_I}\Sigma^{-1}\left(\mu - p\right). \tag{7}$$

The intermediary invests in the mean-variance efficient portfolio: the product of the inverse of the variance Σ^{-1} and the expected return $(\mu - p)$. The position is more or less aggressive depending on the degree of risk aversion, γ_I.

In contrast, the household's demand is given by

$$D_H^* = (\gamma_H\Sigma + \Sigma_{diag}C)^{-1}(\mu - p) - (\gamma_H\Sigma + \Sigma_{diag}C)^{-1}(\gamma_H\Sigma)D_I. \tag{8}$$

The first term of this expression reflects the optimal demand absent any intermediary demand. It balances expected returns with the quadratic risk and investment costs of buying the assets. The second term represents an adjustment for the fact that the household already owns some assets through the intermediary. Importantly, an asset held through the intermediary does not have the same value as the asset held directly, as it avoids the associated trading costs, and therefore in general the substitution between direct and intermediated investment is not one-to-one.[13] Rather, it is given by

$$-\frac{\partial D_H^*}{\partial D_I} = (\gamma_H \Sigma + \Sigma_{diag} C)^{-1} (\gamma_H \Sigma). \tag{9}$$

The effect of the investment cost for this substitution is clear in expression (9). Without investment costs, $C = 0$, assets in and out have the same value, so this substitution is the identity. As investment costs increase, the substitution rate converges to zero. If investing directly in the asset is too expensive, the household does not offset the decisions of the intermediary.

We obtain an expression for prices clearing the market by combining the household's and the intermediary's demands,

$$\mu - p = \gamma_H \Sigma \left(\Sigma + \frac{1}{\gamma_I} \Sigma_{diag} C \right)^{-1} \left(\Sigma + \frac{1}{\gamma_H} \Sigma_{diag} C \right) S. \tag{10}$$

This relation is the nonlinear counterpart to equation (2), which posits a role for intermediary and household risk appetites, γ_I and γ_H, on risk premia. It is interesting to compare these risk premia to those obtained in an economy without any friction. In this case, one would obtain $\mu - p = \gamma_H \Sigma S$. The prices in our economy are distorted relative to this benchmark by $\left(\Sigma + \frac{1}{\gamma_I} \Sigma_{diag} C \right)^{-1} \left(\Sigma + \frac{1}{\gamma_H} \Sigma_{diag} C \right)$. This distortion encodes the potential

[13]This distinction can also have implications for the price of the financial institutions holding the assets. See, for example, Garleanu and Pedersen (2011) and Chodorow-Reich, Ghent, and Haddad (2021).

effect of the intermediary on asset prices, through the effect of the parameter γ_I. The following proposition highlights conditions under which a meaningful notion of "intermediary asset pricing" arises.

PROPOSITION 1: *The intermediary matters for asset prices, that is,* $\partial(\mu - p)/\partial\gamma_I \neq 0$, *if and only if*

$$\gamma_I \neq \gamma_H \quad \textit{and} \quad C \neq 0. \tag{11}$$

The combination of the two frictions of the model is necessary to obtain a role for intermediaries. The first condition captures the idea that, at least in part, intermediary decisions must not exactly reflect the desires of the household. In our simple model, this discrepancy is captured by distinct investment goals, $\gamma_I \neq \gamma_H$. But this condition is not sufficient for intermediaries to matter. It must also be the case that households are limited in their ability to reach their investment objectives on their own. Our model captures this limitation by a nonzero investment cost C. More generally, the key requirement of investment policies to obtain this limitation is that households do not exactly offset the decisions of intermediaries, $-\partial D_H^*/\partial D_I \neq I$.[14]

Now that we have clarified the importance of our two frictions for the notion of intermediary asset pricing, we derive empirical implications of this framework, including the assumption behind the test of Section I.A.

[14]See Internet Appendix Section I.C for a more general discussion.

C. Empirical Implications

Above we discuss how linearizing the model leads to a structure like equation (2): higher values of intermediary or household risk aversion yield higher risk premia. The following proposition goes one step further and shows that the pattern of predictability across asset classes arises in our model and therefore validates our test. To simplify, we assume that Σ is diagonal. We index assets by i and denote by c_i the elements of C.

PROPOSITION 2: *The elasticity of the risk premium to intermediary risk aversion γ_I is increasing in the cost of direct holding c_i, strictly if the intermediary matters for asset prices. The elasticity to household risk aversion γ_H is decreasing in the cost of direct holding.*

To understand this proposition, consider the elasticity of the risk premium to changes in risk aversion:

$$\beta_{i,I} = \frac{1}{\mu_i - p_i} \frac{\partial(\mu_i - p_i)}{\partial \log(\gamma_I)} = \frac{c_i}{\gamma_I + c_i}, \tag{12}$$

$$\beta_{i,H} = \frac{1}{\mu_i - p_i} \frac{\partial(\mu_i - p_i)}{\partial \log(\gamma_H)} = \frac{\gamma_H}{\gamma_H + c_i}. \tag{13}$$

Both of these elasticities are positive, with a role for intermediary risk aversion if and only if there is a nonzero cost of direct investment $c_i > 0$. However, the elasticity is increasing in the cost c_i for intermediary risk aversion while it is decreasing for household risk aversion and flat if there are no frictions (that is, $C = 0$). It is increasing for intermediaries because households offset their trades less in asset classes that are harder to invest in directly. In contrast, the opposite is true for changes in household risk aversion. Figure

2 illustrates this comparison.

[Insert Figure 2 about here.]

Focusing on elasticities rather than simply the derivative of the risk premium with respect to the risk appetite quantities is a useful scaling. Indeed, assets in higher supply or with higher risk have a larger risk premium and therefore will tend to move more in absolute magnitude with risk appetite. Scaling by a baseline level of risk premium cleans out this effect to focus on the role of the financial frictions. Internet Appendix Section I.B discusses a few mechanical properties of this elasticity.

This empirical implication contrasts with other work on intermediaries and predictability that typically focus on a single asset class or do not explicitly consider *relative* predictability (e.g., Haddad and Sraer (2020), Diep, Eisfeldt, and Richardson (2021), Chen, Joslin, and Ni (2019), He, Kelly, and Manela (2017), and Muir (2017), among others). It also differs from the Euler equation approach of linking intermediaries' marginal value of wealth to the cross-section of risk premiums (e.g., Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017)). We discuss this issue in more depth in Section V, but note that in our model, the intermediary Euler equation always holds because intermediaries hold the mean-variance efficient portfolio — equation (7) — regardless of whether intermediaries matter.

II. Data and Empirical Approach

We now turn to empirical measurement of asset returns, cost rankings across asset classes in terms of more versus less intermediated assets, and proxies for intermediary health.

A. Returns

We use asset returns and intermediary state variables that are common in the literature. Specifically, we use excess returns on the market, commodities, credit (CDS), options, sovereign bonds, Treasury bonds, the currency carry trade, and MBS, where we take excess returns over the three-month T-bill where appropriate. These choices are motivated by looking at many large markets where we think intermediation may matter. We start by using the asset returns provided by He, Kelly, and Manela (2017), where we refer the reader to that paper for a thorough description of the series. For CDS, options, sovereigns, and commodities, we take the equal-weighted average in each asset class. Treasury bonds are longer-term Treasury bond returns over the three-month T-bill rate. The credit return is an average across maturities and credit risk. MBS is the Barclay's hedged MBS return index.[15] We use the hedged return to remove exposure to interest rate risk, just as CDS isolates credit risk exposure. Commodities are the equal-weighted average across all commodities available in the He, Kelly, and Manela (2017) data set. The carry trade data come from Adrien Verdelhan. Some of the assets

[15]We thank Peter Diep for help with these data. This series is also available on Bloomberg LUMSER.

are in zero net supply. This is not an issue as long as the asset return is positively correlated with the risk that intermediaries are exposed to (e.g., intermediaries on net will be positively exposed to credit risk and thus the CDS premium will reflect that credit risk is positive on net). In general, our assumption is that the intermediary sector has positive exposure to the asset returns in question such that if their effective risk aversion increases, they will be less willing to bear this risk unless the premium also rises. This positive exposure is strongly supported empirically because betas for these assets classes with respect to the intermediary sector are positive and align with their risk premiums (He, Kelly, and Manela (2017)).[16] For credit, we favor CDSs over corporate bonds because they provide a pure exposure to credit risk and contribute to more variation in intermediation cost across asset classes.[17] Table I reports summary statistics for the asset class returns, including means, standard deviations, and Sharpe ratios. All units are quarterly.

[Insert Table I about here.]

[16]One can also accommodate fixed demand from outside investors in our model to generate the supply that the intermediaries are exposed to. For instance, suppose that some investors want to hedge oil prices or some other risk. Then this demand effectively creates positive supply. Thus, even though there is zero net supply, the intermediaries' risk exposure is positive.

[17]Internet Appendix Section V repeats the analysis for corporate bonds. We return to this comparison later in the text.

B. Intermediary Health

Next, we use variables in the literature that are intended to proxy for intermediary distress or risk-bearing capacity, that is, variables that we believe are correlated with γ_I in our framework. We use two primary measures namely, the broker-dealer leverage factor of Adrian, Etula, and Muir (2014, AEM) and the intermediary equity measure of He, Kelly, and Manela (2017, HKM). Both of these measures have been argued, theoretically and empirically, to capture intermediary distress, and both are linked to risk premiums. We take annual log changes of each state variable. In our main results, we standardize the AEM and HKM measures and take the average, so as to take the average of the risk-bearing capacity measures used in the literature. We refer to the resulting measure as risk-bearing capacity, and the negative of this measure as effective risk aversion. Again, we emphasize that we do not provide deep theory for what determines intermediary distress or risk-bearing capacity, although these variables are motivated in such a way elsewhere. Rather, our goal is to take off-the-shelf measures from the literature to test our main hypothesis.

Finally, we also include variables that we think may capture aggregate or household risk aversion, such as the consumption-wealth ratio proxy of Lettau and Ludvigson (2001) and the habit measure (surplus consumption) of Campbell and Cochrane (1999). Specifically, Lettau and Ludvigson (2001) construct the variable *cay* using aggregate consumption, labor income, and asset wealth. This last component in particular relies on valuations, and therefore would naturally also capture aggregate fluctuations in the willingness to invest in risky assets. We do not take a strong stand on these variables in terms of corresponding perfectly to household risk aversion, although we consider whether including them in our regressions affects our results. This is useful because our theory does have a differential prediction about how shocks to household risk aversion should interact with risk premia, so this provides a nice additional test of the model.

Figure 3 plots the time-series behavior of the intermediary effective risk aversion proxy (green line), as well as the household effective risk aversion series from the surplus consumption measure (red line). According to these measures, periods of high intermediary risk aversion often coincide with periods of high household risk aversion, the financial crisis of 2008 being a striking example. The two series also exhibit some amount of independent variation that we exploit later in the paper.

[Insert Figure 3 about here.]

C. Ranking of Assets by Degree of Intermediation

Our empirical tests require that we rank assets by the willingness of households to hold them. Dispersion along this dimension is important for our empirical design because we exploit the fact that assets that are more specialized (i.e., held by intermediaries) respond more to intermediary health. We identify which assets are more intermediated using several approaches. Specifically, we consider holdings data, volume of trade accounted for by institutions (focusing in particular on dealers), as well as the direct costs faced by households (we use the fees charged by ETFs by asset class; we also discuss other physical costs that households face in each market).

Importantly, all of these approaches yield roughly similar rankings of which asset classes are more or less intermediated. We report our rankings in Table II. Stocks always appear least intermediated. At the other extreme, CDS appear most intermediated. This makes sense: one needs an International Swaps and Derivatives Association (ISDA) master swap agreement to trade CDS, an agreement that a household would find close to impossible to enter into. The remainder of the ordering, from less to more intermediated, is roughly government bonds, options, sovereign bonds (emerging market), commodities, FX, MBS, and CDS. We emphasize that we take a data-driven approach to construct these rankings, although we do not take an overly strong stance on the exact ordering (e.g., one could swap some of the adjacent pairs). We return to this issue in our empirical tests.

[Insert Table II about here.]

C.1. Holdings and Volume Data

By revealed preferences, relative holdings of assets directly by households and through intermediaries offer a proxy for the cost of intermediation. For example, in our simple model, we obtain $\frac{D_{I,i}}{D_{H,i}} = \frac{c_i+\gamma_H}{\gamma_I-\gamma_H}$, which is increasing in the cost c_i. We first study holdings based on FoF data for 2016; similar results obtain using the Survey of Consumer Finances (SCF).[18] Using the FoF, we

[18]Compared to the FoF, the SCF offers two advantages in measuring holdings of households. First, we can focus on higher-income households, which are more active in asset

construct holdings of stocks, Treasuries, foreign and corporate bonds, and MBS as a percentage of total assets for households and nonprofits (HH) as well as for broker-dealers and commercial banks. We then compare the ratio of HHs' holdings of stocks to those of broker-dealers or banks and likewise for the other asset classes. We find that households hold far more equities relative to intermediaries, while they hold fewer Treasuries and far fewer corporate and foreign bonds and MBS. However, the data do not contain holdings of more specialized asset classes such as CDS. Moreover, the FoF computes household holdings as a residual from other sectors. In particular, this measure includes the holdings of hedge funds, which would be better classified as intermediaries under our approach.

Our next data source is the BIS derivatives semiannual report.[19] We use BIS data from year-end 2016. These data contain total gross notional positions in each market, specifically, total gross positions by reporting dealers, other financial institutions, and nonfinancial institutions. We use the sum of reporting dealers and other financial institutions relative to totals; similar results obtain when using reporting dealers as a fraction of the total. These positions are available for commodities, CDS, FX, and equity derivatives, which we use to proxy for equity index options in our sample. Our rankings order equity options, commodities, FX, and CDS as least to most intermediated.

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markets. Second, while FoF lumps households with nonprofits, some of which have significant assets, SCF does not. However, SCF is a survey and hence is subject to other concerns.

[19]See https://www.bis.org/statistics/derstats.htm.

C.2. Value-at-Risk Data

One concern with the rankings above is that they may not capture true "exposures" to the various asset classes. For example, if households hold very low-risk stocks and intermediaries held very high-risk or high-beta stocks, the fractions above may miss this. To address this concern, in the context of the model we can focus on relative wealth betas for each asset class, which we refer to as exposures.

Empirically, we gain insight into intermediaries' exposures by looking at large primary dealers' annual 10Ks, which report VaR across four asset classes — commodities, equities, interest rates, and FX — and therefore allow us to construct effective relative dollar exposures to each asset class.[20] VaR reports tail risk: a dollar amount that losses would not be expected to exceed 99% of the time. Using data for year-end 2016, we convert this number into relative exposures by assuming a normal distribution for each asset class and normalizing by the standard deviation of the asset class returns from our sample. We then normalize each asset class using a measure of total supply. For equities and bonds, we use the relative sizes of the equity and fixed income markets in the U.S., roughly \$15 trillion and \$50 trillion, respectively; our numbers for bonds are unchanged if we use only U.S. Treasuries outstanding. For commodities and FX, we use the gross market value from the BIS to normalize exposures. Our results continue to hold: relative to the sizes of the markets, dealer exposures are smallest for equities, then bonds, then commodities, and finally FX. The absolute exposures are largest for fixed

[20] Internet Appendix Section II lists these banks.

income, but importantly this market is quite large and much of this risk is born by other investors, so it is not as large relative to the total quantity of bonds outstanding. This ranking thus gives similar results to using the position data as above.

C.3. Direct Measures of Costs

We next study household ease of access to different asset classes by analyzing fees for ETFs as captured by expense ratios in the ETF database.[21] While these products would not have been available to households over much of our sample, looking at ETF expense ratios helps us gauge households' current cost of investing in these assets, and it is likely that they reflect households' historical difficulty in investing in the corresponding asset classes as well. We note that this analysis takes the cost of accessing asset classes literally. In reality, households may not invest in some assets due to complexity or other characteristics not captured by actual direct costs.

We take the average expense ratio by asset class — Stocks, Government Bonds, Emerging Markets Bonds (our best proxy for sovereign bonds), Currency, Commodities, Volatility, and MBS. We use volatility to proxy for our option straddle strategy, which is a bet on volatility.[22] There is no category for CDS, since very few ETFs trade CDS. Accordingly, we supplement this

[21] See http://etfdb.com/etfdb-categories/.

[22] We note much of the Volatility ETFs trade VIX futures directly, and these strategies are different although they are exposed to the same underlying risks (Dew-Becker et al. (2017)).

analysis by studying two ETFs that specialize in CDS.[23]

We need to normalize the expense ratios in each asset class, just as we do in our simple model. For example, while government bond ETFs are safer, lower-return funds and thus a high expense ratio means that post-fee returns are likely to be particularly low, this is less critical for equity ETFs. We normalize expense ratios by the standard deviation of returns in each asset class. Alternatively, we could normalize by the mean return in each asset class. The latter approach gives similar results but is less desirables as means are much less precisely estimated than standard deviations.

Our approach based on ETF data implies the following ordering, from easiest to hardest to access: stocks, Treasuries, sovereign bonds, currencies, commodities, options, MBS, and CDS. This ordering is largely consistent with our main ranking.

C.4. Other Differences Across Asset Classes

While we focus on heterogeneity in households' ease of access, asset classes differ along other dimensions as well. For example, some of the more intermediated asset classes such as MBS and CDS are less liquid than the stock market or currency markets, and as a result are associated with larger transaction costs. To the extent that liquidity risk is reflected in expected returns, this heterogeneity should be seen in the return data. Intermediaries would still play a central role under this mechanism, but for reasons other than those

[23]ProShares offers both a long and a short ETF for North American high-yield CDS (i.e., one can effectively buy or sell protection). These ETFs were launched in 2014 as the first CDS ETFs.

that are the focus of our theory. More broadly, the various asset classes also trade different sources of economic risk.

The presence of heterogeneity across asset classes beyond the cost of direct access is not a challenge for our empirical strategy in and of itself. Rather, these other forces could confound our results only if they change disproportionately for the harder-to-access asset classes in times of high intermediary risk aversion. For example, it would have to be the case that not only is liquidity risk more pronounced for the more intermediated asset classes, but it increases more in periods of high intermediary risk aversion for these asset classes. We empirically address the possibility of such patterns in Section IV.A.

III. Empirical Results

A. *Intermediary Health Forecasts Returns*

A.1. Methodology

We estimate the following linear equation using quarterly data for each asset class:

$$r^{\sigma}_{i,t+1} = a_i + b_i \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}, \tag{14}$$

where $\tilde{\gamma}_{I,t}$ is our standardized measure of intermediary risk aversion and $r^{\sigma}_{i,t+1}$ is the excess return of asset class i between quarter t and $t+1$, divided by its full-sample volatility. As we discuss above, this scaling of excess returns makes predictive coefficients comparable across asset classes. Ideally we would normalize returns by their unconditional risk premium. This approach poses additional statistical challenges, however, which we come back to in the next section. Notice that while scaling returns by a constant affects the magnitude of the coefficient estimates, it does not influence t-statistics and R^2s.

We implement the Hodrick (1992) reverse-regression approach to obtain standard errors for our coefficient estimates. In addition, we compute p-values for the predictive coefficient using parametric bootstrap to account for small sample bias (for example, Stambaugh (1999)). Specifically, we estimate a restricted VAR for quarterly excess returns and intermediary health under the null of no return predictability by intermediary health.[24] We assume that the joint distribution of innovations in the VAR corresponds to their empirical distribution. We then draw 5,000 samples from this estimated process to obtain a distribution of reverse-regression t-statistics. We report the p-value of our estimated t-statistic relative to this bootstrapped distribution. Both the asymptotic standard error and the p-value are informative: the asymptotic standard error is robust to the specifics of the data-generating process, while the p-value handles finite-sample issues conditional on a parameterized data-generating process.[25]

[24]When including additional controls to the regression, such as in Table IA.XV, we let these other variables predict returns in the VAR as well.

[25]Table IA.III reports Newey-West standard errors allowing for eight-quarter lags. Results are stronger with this approach, though a concern is that this procedure can over-reject the null in small samples (see, for example, Ang and Bekaert (2006)).

A.2. Main Predictive Regressions

Table III presents our predictability results. First, we find that intermediary effective risk aversion generally positively predicts risk premiums across the asset classes considered. When intermediary health is poor, and intermediaries' effective risk aversion is high, risk premia going forward are generally higher.[26] Since we normalize by asset class volatility, and because our predictor variable is standardized to have unit variance, the coefficients indicate an increase — in Sharpe ratio units — to a one-standard-deviation increase in the intermediary risk aversion measure. Sharpe ratios for the different asset classes are fairly similar and typically around 0.25 quarterly. Therefore, the typical coefficient of 0.2 implies a bit less than a doubling of Sharpe ratios, an effect that is economically large.

[Insert Table III about here.]

Second, we find that the degree of predictability, as measured by the coefficient, significance level, or (adjusted) R^2, generally increases as we go from left to right, that is, as we go from less to more intermediated asset classes. Predictive power tends to be lower for stocks (coefficient 0.12, R^2 0.8%) and higher for more intermediated asset classes such as MBS (coefficient 0.30, R^2 7.8%) or credit (coefficient 0.57, R^2 31.6%). Of the eight asset classes, slope coefficients for six of the asset classes — the more intermediated asset classes

[26] He, Kelly, and Manela (2017) also provide evidence of common predictability across asset classes.

— are significant at conventional levels. Further, the magnitudes of the coefficients for all six of these asset classes are larger than those for stocks or Treasuries. Figure 4 shows the increasing pattern of slope coefficients b_i in a scatter plot where the x-axis corresponds to our ranking of less versus more intermediated asset classes. Panel B of Figure 5 shows a similar increasing pattern for the regression R^2. This is not surprising — because the volatility of returns is equal to one under our normalization, and the intermediation measure is standardized, the (unadjusted) R^2 is the square of the predictive coefficient.[27]

[Insert Figure 4 about here.]

The last row of Table III reports the elasticity of the risk premium to a one-standard-deviation increase in intermediary risk aversion, given by $b_i/\mathbb{E}(r_i^\sigma)$; Panel A of Figure 5 plots the elasticities.[28] We again observe a strong increase in elasticities as we move from less to more intermediated assets. We revisit this pattern of increasing predictability and its statistical properties after discussing robustness of the predictive regressions.

[Insert Figure 5 about here.]

[27]Formally, $R^2 = var(b_i \tilde{\gamma}_{I,t})/var(r^\sigma_{i,t+1}) = b_i^2$.

[28]Note that it is irrelevant that we first normalize returns by their volatility when computing this elasticity. That is, the elasticity can be equivalently measured as the coefficient b_i^r in $r_{i,t+1}/E[r_{i,t+1}] = a_i^r + b_i^r \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}$, where $r_{i,t+1}$ is the raw excess return.

A.3. Robustness of Predictability

We assess the robustness of the predictive regressions along several dimensions. To save space, we describe the results here but leave the tables to the Internet Appendix. We first examine whether our particular sample period, that includes an episode of more severe intermediary distress, drives our results. To do so, we begin by dropping the financial crisis (2007 to 2009) from our analysis. Similar results obtain (Table IA.IV). We also rerun the analysis using only data after 1990 (Table IA.V), which reduces the heterogeneity in sample length across our asset classes. Our results continue to go through. Finally, we examine whether the predictability changes during periods of low intermediary health by estimating different coefficients for values of $\tilde{\gamma}_I$ above and below its mean (Table IA.VI). We find that splitting the sample in half results in limited statistical power and no statistically different results across periods of high or low intermediary health.

Another concern relates to our choice of intermediary health measures. Our baseline uses an average of the HKM and AEM intermediary factors without taking a strong stand on the drivers or and measurement of intermediary health. We show that several alternative ways of proxying for intermediary health lead to similar conclusions. Specifically, Figures IA.3 and IA.4 plot results when we split our intermediary health measure into the HKM and AEM components separately — Tables IA.VII and IA.VIII present the regression coefficients. We find that both measures contribute to our main result, although results are stronger for the AEM measure. Figure IA.5 uses the log levels of the AEM and HKM factors rather than annual log changes (we continue to average the two after standardizing them). In IA.2 we plot the pattern of predictability when we use the GZ spread of Gilchrist and Zakrajek (2012) to proxy for intermediary risk aversion instead of the AEM or HKM measures. Gilchrist and Zakrajek (2012) argue that this spread captures the health of the financial sector and show that it closely follows dealer CDS spreads in their sample.

Finally, in Internet Appendix Section V, we examine corporate bond returns as an alternative measure of credit returns to CDS. We find strong return predictability for corporate bonds, albeit the return predictability is somewhat lower in magnitude than for CDS — see Table IA.I. This result makes sense because corporate bonds contain both credit and duration risk.

B. *Do Intermediaries Matter?*

B.1. Interpretation of the Pattern across Asset Classes

Figures 4 and 5 show an increasing pattern of predictability: more intermediated asset classes are more predictable by intermediary health. Fitting a regression through these estimates — the red line — implies that the most intermediated asset classes have a predictive coefficient that is about 0.25 greater than the least intermediated asset classes.[29] In Table IA.II we show that capturing the degree of predictability across asset classes in a panel regression with an interaction term for more intermediated asset classes gives the same estimate for this slope. Elasticities experience an increase of a com-

[29]This slope across asset classes is the coefficient B in regression $b_i = A + B \times c_i + u_i$, where c_i grows linearly from zero to one.

parable order of magnitude (recall that the typical normalized mean return is about 0.25, so elasticities should be about four times larger than the predictive coefficients). Finally, it could be the case that this increasing pattern is driven by a single asset class with an extreme value. Figure IA.6 shows this is not the case: the result holds even if we remove any single asset class.

The consistent increase in predictability is our main empirical result. This observation supports the view that intermediaries matter for risk premia, particularly for the most intermediated asset classes. If the predictability that we measure reflected changes in household risk aversion, we would instead observe less predictability for more intermediated asset class. Importantly, our estimates do not rule out the possibility that intermediary health partially proxies for household risk aversion and that this variation also matters for asset prices. Instead, they tell us that the increasing effect of intermediaries on risk premia as we move from least to more intermediated asset classes dominates the decreasing effect from households. As a result, we are not only rejecting the null hypothesis that intermediaries do not matter, but also offering a quantitative lower bound on their effect. It is tempting to go one step further and use equation (12) to recover intermediation costs, but we recover bounds on the elasticity to actual intermediary risk appetite only up to a multiplicative constant. This limitation arises because we only know that our proxy for intermediary health is positively related to the actual intermediary risk appetite γ_I — we do not know the strength of this relation.

B.2. Statistical Properties of Our Test: A Bayesian Approach

Naturally, this bound comes with standard errors. We next assess the statistical properties of this increasing pattern of predictability. We ask with what degree of statistical confidence we can conclude that more intermediated asset classes are more predictable by intermediary health. The main concern we address is uncertainty associated with estimating the mean returns.

We take a Bayesian approach to this question; Internet Appendix Section III provides technical details. We start by providing the counterpart to equation (14) where excess returns are not scaled:

$$r_{i,t+1} = a_i + b_i \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}. \tag{15}$$

We choose a prior on the coefficients $\{(a_i, b_i)\}_{i=1,\ldots,N}$ in this regression and consider various properties of their posterior distribution given our sample. Specifically, the joint distribution of these coefficients implies a joint distribution of the elasticities b_i/a_i.[30] We ask what is the posterior probability that the slope across elasticities – the red line in our figures – is positive, or that the average elasticity for more intermediated asset classes is large relative to that for less intermediated asset classes. For this second type of comparison, we consider the case of Stocks and Treasuries relative to CDS and MBS, Stocks and Treasuries relative to all other asset classes, and Stocks,

[30]We demean $\tilde{\gamma}_{I,t}$ for the sample of each asset class so that the coefficient a_i estimates the unconditional mean return. Demeaning the right-hand side of the regression does not affect statistical inference under the Bayesian approach below or under the frequentist view, and thus doing so is without loss of generality.

Treasuries, and Options relative to all other asset classes.

We assume that the errors $\epsilon_{i,t+1}$ are normally distributed, are uncorrelated over time, and have known cross-sectional variance-covariance matrix Σ_ϵ given by the variance-covariance matrix of OLS residuals.[31] These assumptions correspond to the Seemingly Unrelated Regression framework of Zellner (1962). We focus on truncated multivariate normal priors, which are conjugate with our assumptions on residuals. For the vectors $a = (a_1, ..., a_N)$ and $b = (b_1, ..., b_N)$, we assume means $\bar{a}\sqrt{diag(\Sigma_\epsilon)}$ and $\bar{b}\sqrt{diag(\Sigma_\epsilon)}$ and variances $\sigma_a^2\Sigma_\epsilon$ and $\sigma_b^2\Sigma_\epsilon$, where $\bar{a}$, $\bar{b}$, σ_a, and σ_b are scalar. Finally, we assume that the vectors a and b are independent of each other. Intuitively this prior is expressed in Sharpe ratio units.[32] For the unconditional mean a, Pástor (2000), Pástor and Stambaugh (2000), and Kozak, Nagel, and Santosh (2020) show that this choice of prior — scaled by the variance of realized returns — ensures reasonable return properties.[33] The arguments in Haddad, Kozak, and Santosh (2020) show that these ideas extend to the case of predictability, justifying the use of this prior for b as well. In the absence of truncation, and when σ_a and σ_b are large, the Bayesian posterior has mean and variance that correspond to both the point estimate and the standard errors of the frequentist approach. Throughout, we assume that the prior is centered around a quarterly Sharpe ratio of 0.25 (corresponding to 0.5 annually) and

[31] In Internet Appendix Section III.C, we show that uncertainty about this variance-covariance matrix does not play a quantitatively meaningful role in our analysis.

[32] A small distinction with our previous analysis is that these scalings are in terms of the average conditional Sharpe ratio rather than the unconditional Sharpe ratio.

[33] For example, the expected Sharpe ratio will be bounded above irrespective of Σ_ϵ.

no predictability: $\bar{b} = 0$, $\bar{a} = 0.25$. We choose a loose $\sigma_b = 1$ and impose no truncation for b_i. These assumptions are mild and imply that the prior probability of increasing elasticities across asset classes is always 50%: we are never generating an increasing pattern of predictability through the choice of prior. We now turn to two sets of more meaningful assumptions for statistical inference.

First, we impose a positive lower bound on a_i. The computation of elasticities involves dividing by the unconditional mean a_i. If the distribution of a_i goes through zero, this will yield arbitrarily large positive and negative values of the elasticity.[34] It therefore appears necessary to bound a_i away from zero to obtain reasonable statistical properties. We do so by imposing a lower bound $\underline{a}\sqrt{diag(\Sigma_\epsilon)}$ on these coefficients, with $\underline{a}$ scalar. This assumption corresponds to a lower bound $\underline{a}$ on the average Sharpe ratio for each of the asset classes. Naturally, it is important to ask what such an assumption means economically. There are three ways to interpret this bound. First, it is an economic restriction: broad asset classes are all likely to receive a positive risk premium because they capture aggregate risk.[35] Second, it is an empirically motivated assumption: across many samples, an extensive literature documents positive premia for these asset classes; we discuss this evidence in Internet Appendix Section IV. Third, the doubtful reader can stress that

[34]Furthermore, if the distribution of a_i is nonzero and continuous at the point 0, the posterior mean of the elasticity does not exist.

[35]Campbell and Thompson (2008) argue for this type of restriction. Our approach is less stringent: Campbell and Thompson (2008) bound conditional expected returns at each point in time, while we impose a bound only on unconditional expected returns.

our conclusions are part of a joint hypothesis framework: we draw economic conclusions under the assumption that unconditional Sharpe ratios have a lower bound.

Figure 6 plots the posterior probability of decreasing elasticities as a function of the truncation level for the quarterly Sharpe ratio. The thick black line is the posterior probability that the slope across elasticities is negative; lower values favor our theory, in the spirit of a p-value for the null of no pattern. Without getting rid of negative Sharpe ratios, in particular, the values close to zero, the inference about this slope is rather imprecise, with probabilities around 11%. However, as soon as one imposes a positive bound on the Sharpe ratio, the probability drops sharply, with values under the 5% threshold. For example, a reasonable lower bound of 0.05 gives posterior probabilities of around 3%. The pattern for our three other comparisons is similar. Comparing the extremes of Stocks and Treasuries with Credit and MBS (solid black line) yields even tighter conclusions, while comparing Stocks, Treasuries, and Options with the rest of the sample (dashed line) gives slightly higher probabilities. The only noticeably large values, while still around 10%, occur when comparing Stocks and Treasuries with the remainder of asset classes. In summary, we conclude with a high degree of confidence that more intermediated asset classes are more predictable by intermediary health.

[Insert Figure 6 about here.]

One might want to go further in terms of statistical regularization. Even abstracting from the issue of dividing by zero, uncertainty about unconditional means contributes to uncertainty about the patterns of predictability. This phenomenon is amplified by the fact that we estimate means for multiple asset classes. To regularize our estimates, a natural approach is to impose some form of shrinkage towards a common value. Following this approach, we shrink Sharpe ratios of all of our asset classes towards a common value.[36] In our Bayesian framework, this corresponds to tightening the priors on average Sharpe ratios around a common value, namely, our mean $\bar{a} = 0.25$. Why 0.25? This number corresponds to the well-known estimate of an annual Sharpe ratio of 0.5 for the equity market, which is roughly the average Sharpe ratio across asset classes in our sample and is justified by an extensive body of empirical work studying long historical samples for these asset classes. For example, Gorton and Rouwenhorst (2006) find that commodities have a Sharpe ratio similar to that of stocks, and Asvanunt and Richardson (2016) highlight the comparable Sharpe ratios of stocks, Treasuries, and credit; see Internet Appendix Section IV for more discussion. We also note that the specific choice of $\bar{a}$ is not critical for our results. Shrinking all the way to any common value corresponds to comparing directly predictive coefficients scaled by volatility $b_i/\sqrt{\Sigma_{\epsilon,ii}}$ in terms of the pattern of predictability

[36] Pástor (2000) and Pástor and Stambaugh (2000) follow this approach. Kozak, Nagel, and Santosh (2020) assume that Sharpe ratios are proportional to variances in order to impose the absence of near-arbitrage across the thousands of available stocks. Our setting is different in that we focus on a small set of asset class index returns, which could all have sizable Sharpe ratios.

across asset classes.[37] This extreme provides an economic interpretation to the "model-free" comparison of coefficients that we report in the previous section: we are comparing elasticities under the assumption that all asset classes have the same unconditional Sharpe ratio.

[**Insert Figure 7 about here.**]

Figure 7 illustrates what happens when we implement the shrinkage by bringing σ_a towards zero. Panel A reports the median as well as 5th, 10th, 90th, and 95th percentiles for the posterior of the cross-sectional slope of elasticities. First, one can observe the phenomenon of shrinkage. For large values of σ_a, the estimate corresponds to what one obtains using the OLS estimates of b_i and a_i. As σ_a goes to zero, the median estimate is reduced to a lower value, which corresponds to the slope when replacing a_i by $0.25\sqrt{\Sigma_{\epsilon,ii}}$. In this case we estimate a slope of around one, which is about four times larger than the slope in Figure 4 since we divide coefficients by $\bar{a} = 0.25$. Second, this approach brings regularization because shrinkage reduces the uncertainty caused by estimation of mean returns. The distribution of the slope estimate tightens. As a byproduct, inference about patterns of predictability will be much stronger when using some shrinkage. Panel B confirms this view by reporting the posterior probability for our measures of increasing slope. If we assume that all Sharpe ratios are equal to 0.25, then the probabilities

[37]Relative to our earlier results, the shrunken estimates multiply all predictive coefficients by the constant $1/\bar{a}$ so that all coefficients are four times larger, but do not change the relative pattern across asset classes.

of negative slope are all well below 1%. Of course, this case is an extreme form of prior, but imposing weaker assumptions already achieves meaningful regularization. For example, assuming $\sigma_a = 0.05$, that is, that Sharpe ratios mostly lie between 0.15 and 0.35, already reduces posterior probabilities of a negative slope to very low values. In summary, we find that if one is willing to impose views on unconditional Sharpe ratios to regularize elasticity estimates, our conclusions on patterns of predictability are reinforced. It is important to repeat that these stronger views are not assuming the pattern of predictability, but rather incorporate additional plausible economic assumptions on unconditional properties of returns.

C. *The Role of Households*

Our main argument also makes predictions about proxies for household risk aversion in influencing risk premia. Specifically, when intermediaries matter, an increase in household risk aversion should, if anything, have a larger effect for assets that are more easily accessed and hence more directly held by households. While we emphasize that our main tests do not require that we take a stand on the behavior of household risk aversion, we explore this possibility using two proxies for household willingness to bear risk often used in the literature: the aggregate consumption-wealth ratio, *cay*, of Lettau and Ludvigson (2001), and the habit measure of Campbell and Cochrane (1999).

[Insert Figure 8 about here.]

Figure 8 plots the predictive coefficients for intermediary risk aversion and household risk aversion, measured using *cay*; we report the regression results in Table IV. Panel A illustrates that controlling for household risk aversion does not affect the strongly increasing pattern of predictive ability of intermediary health as we move towards asset classes that are more difficult to access. In Panel B, we see that, if anything, the coefficients on household risk aversion exhibit the opposite pattern: they are mildly decreasing as we move from assets that are more to less directly held by households. As an aside, this result suggests that there is nothing inherently mechanical in finding stronger predictability as we move along our ranking. Figure IA.7 shows the pattern of coefficients in our predictive regressions when we include the habit measure in our regressions; Table IA.XI reports the regression results. We again observe a distinctly decreasing pattern of predictability. Finally, we consider the dividend-price ratio on the CRSP value-weighted stock portfolio. While less directly related to aggregate household conditions, this measure provides an alternative proxy for valuations in the more frictionless asset class — stocks. A similar pattern emerges: we observe a strongly increasing response to intermediary risk aversion, and a mild decreasing response to this proxy for household risk aversion; Figure IA.8 and Table IA.XII show the results.

[Insert Table IV about here.]

The results above suggest that households influence risk premiums, but in a way that is distinct from the role of intermediaries. Here again, it is worth pointing out that our proxies are imperfect: the household variation we study may be affected by changes in intermediary health in the same way that the intermediary variation we study is potentially affected by changes in household risk aversion. It is nevertheless comforting that aggregate risk aversion proxies do indeed appear to line up with risk premiums as predicted by the model. The independent variation we observe between the two types of proxy allows us to tease out the distinction between the two sides of our mechanism. Moreover, this pattern highlights two distinct components of risk premium cycles.

D. Decomposing Variations in Expected Returns

We use the results above to decompose variation in risk premiums into the part due to intermediaries and the part due to households. For each asset class, the predictive regression provides a baseline estimate of risk premium variation. We use the lower bound implied by coefficient comparison across asset classes to separately quantify the role of intermediaries and households. These bounds, even when combined, do not explain all of the variation in the risk premium: some measured variation in the risk premium remains that we cannot trace specifically to one of these two sources.

We implement the decomposition as follows. We start from the predictive regression coefficients $b_{i,I}$ and $b_{i,H}$ for each asset class — the points in Figure 8. To account for the patterns across asset classes, we fit linear slopes across these coefficients,

$$b_{i,I} = A_I + B_I \times c_i + u_{I,i} \tag{16}$$

$$b_{i,H} = A_H + B_H \times c_i + u_{H,i}, \tag{17}$$

where c_i increases linearly from zero to one. This linear fit corresponds to the red lines in Figure 8; we establish statistical significance for the pattern of coefficients on intermediary risk aversion across assets in Section III.B. Using this linear model, we obtain an estimate of the total variance of the risk premium for each asset class,

$$\sigma^2_{Total} = \sigma^2 \left(\mathbb{E}_t(r^{\sigma}_{i,t+1})\right) = \sigma^2 \left(\left(A_I + B_I \times c_i\right) \tilde{\gamma}_{I,t} + \left(A_H + B_H \times c_i\right) \tilde{\gamma}_{H,t} \right), \tag{18}$$

where we compute the variance of the right-hand-side quantity in our sample. Of course, this regression may include an incomplete set of predictors, and there may be more overall variation in risk premia in these asset classes. That said, we are reluctant to include more variables, because their choice would be somewhat arbitrary and could artificially inflate risk premium variation through overfitting. In addition, the high R^2s that we obtain suggest it is unlikely that much more predictability remains. Alternatively, one could interpret our decomposition as the fraction of *our measured variation* in risk premium that can be traced back to intermediaries or households.

We next quantify how much variation we can attribute to intermediaries. In the framework of Section I.A, the lower bound on the role of intermediaries comes from the stronger predictability of the more intermediated asset classes. The bound holds even if we have an imperfect proxy — see also the derivation in Internet Appendix Section I.A. This pattern is driven by the positive slope B_I of the fit across asset classes: $\sigma^2_{Intermediaries} \geq \sigma^2\left(\left(B_I \times c_i\right)\tilde{\gamma}_{I,t}\right)$. Conversely, the role of households is driven by the decreasing predictability across asset classes, that is, negative B_H: $\sigma^2_{Households} \geq \sigma^2\left(\left(-B_H \times (1 - c_i)\right)\tilde{\gamma}_{H,t}\right)$. For example, we cannot identify any variation due to intermediaries in the least intermediated asset class with $c_i = 0$, Stocks. Conversely, we cannot identify any variation due to households in the most intermediated asset class with $c_i = 1$, Credit.

Figure 9 presents the results. The red (blue) bars indicate the fraction of variation in risk premia for each asset class attributable to households (intermediaries) $\sigma^2_{Households}/\sigma^2_{Total}$ $(\sigma^2_{Intermediaries}/\sigma^2_{Total})$, while the gray region indicates variation we cannot confidently attribute to either households or intermediaries. The decomposition suggests that we can attribute at least 60% of the variation in CDS risk premia to intermediaries, with the variation declining by asset class but still substantial for FX, commodities, and sovereign bonds. We can attribute at least 40% of risk premium variation in stocks to households, with this variation declining as we move to more intermediated asset classes. We again stress that these are *lower* bounds: the gray area in the middle is not necessarily indication of a third force, but rather variation not attributable to either category using our empirical strategy.

[Insert Figure 9 about here.]

Figure IA.9 repeats this exercise using elasticities rather than the predictive coefficients normalized by volatility. The decomposition is similar, with a somewhat larger role for intermediaries. Figure IA.10 assesses the sensitivity of our inference to the assumption of a linear structure across c_i. We use a local regression, a quadratic specification, and a cubic specification. The pattern and magnitude of variation in the fitted curves does not change much, with a stronger increase for intermediary risk aversion than for household risk aversion; these estimates lead to a variance decomposition similar to our linear baseline. Finally, while the decomposition that we report is based on our best estimates of the lower bound, one should remember that these estimates come with uncertainty. Table IA.XIII builds on the approach of Section III.B to capture this uncertainty. The strong role of intermediaries comes with relatively high precision, for example, with an interquartile range for Credit between about 45% and 90%. In contrast, the effect of households, in addition to being weaker, is more imprecise.

Finally, note that we implement an *unconditional* decomposition: our empirical model assumes that predictive coefficients and the variance of predictors are constant over time. With more data — recall that our sample does not allow us to detect variation in the predictive coefficient — or by imposing a more structural view one can imagine entertaining variation in these quantities over time. For example, periods of poor intermediary financial health, $\tilde{\gamma}_I > 0$, experience about a 60% higher standard deviation in $\tilde{\gamma}_I$ than periods of good health, while the standard deviation of $\tilde{\gamma}_H$ decreases by about 10%. This suggests a larger role of intermediaries in the variation in risk premia during episodes of poor financial health of the financial sector, in line with the model of He and Krishnamurthy (2019).

IV. Additional Evidence

A. The Role of Variation in Risk

So far we only consider movements in intermediary and household risk aversion (and use the data to distinguish these two), but other determinants of returns may also change. One salient possibility is that risks vary over time. This may be a particular concern for some of the assets we study with nonlinear payoffs (e.g., options or credit). For example, in our model, the covariance matrix of asset payoffs might fluctuate. Variation in risk is a concern if more intermediated asset classes become riskier when intermediary distress increases. We empirically explore this possibility in several ways. Specifically, we study the effect of various notions of risk, including volatility, skewness, and time-varying betas on standard asset pricing factors, which include market risk and liquidity risk, among others.

First, we ask whether intermediary health predicts *future* risk in a way that lines up with the pattern of risk premia. To do so, we run the same predictive regressions as our main analysis (Table III) but on the left-hand side we replace future excess returns with squared future returns. A positive coefficient indicates higher expected variance when intermediary risk aversion is high. Table V, Panel A reports the coefficients from this regression to assess how intermediary health predicts risk; Figure IA.11 plots their values. Importantly, the coefficients do not exhibit an increasing pattern. The more intermediated asset classes do not appear to be relatively riskier in times of high intermediary distress, so future risk does not qualitatively explain the increasing pattern of risk premiums that constitute our main result. In addition, the coefficients are on average slightly positive but much smaller in magnitude than the elasticities documented earlier. In particular, in response to a one-standard-deviation increase in intermediary risk aversion, variance increases by about 20% while the risk premium increases by close to 100%. This implies that changes in risk cannot account for the increase in the average risk premium. Measures of risk beyond variance could be relevant to risk premia. In Figure IA.13, we study downside risk and skewness in addition to variance. We find no support for the idea that crash risk or left skewness increases for the more intermediated asset returns when intermediary risk aversion is high. If anything, the results go slightly in the opposite direction, though are not large quantitatively.

[Insert Table V about here.]

Our assets might also exhibit nonlinear exposures to other aggregate risk factors that variance and skewness do not capture. This would imply variation in conditional betas, and therefore expected returns, even absent variation in total risk. To assess whether such behavior is driving our results, one must take a stand on what the relevant *economic* risk factors are. Indeed, without such a stance, one could just reverse engineer the stochastic discount factor that prices these eight asset classes and seemingly explain risk premia, even though this would be a mechanical result.[38] Instead, the

[38]See, for example, Kozak, Nagel, and Santosh (2018) for a discussion of the lack of interpretability of reduced-form factor models.

interesting question is whether changes in exposure to some economic sources of risk is the reason expected returns are changing. One such risk could be captured by the aggregate stock market return. For example, because stocks are the asset class with the lowest cost, their return might reveal frictionless economic risk. In Panel B of Table V, we examine whether intermediary risk aversion predicts the covariance of returns with the market.[39] While the covariance with the market appears to increase across asset classes somewhat in times of high intermediary risk aversion, the magnitudes are small relative to the change in expected returns that we document. More importantly, the increases are *less* pronounced for more intermediated asset classes, ruling out these variations as an explanation for our main results. In Panel C, we consider exposure to the liquidity factor of Pástor and Stambaugh (2003). As we discuss earlier, differential exposures to liquidity could be an alternative mechanism through which intermediaries affect risk premia. However, changes in exposure to liquidity are tiny and do not exhibit an increasing pattern, and thus time-varying exposure to liquidity risk does not appear to explain our findings.

An alternative way to assess whether time-varying exposures drive our findings is to absorb such variation in the regression predicting returns. This approach allows us to consider multiple sources of conditional risk simultaneously. To do so, we follow the framework in Shanken (1990) and explicitly allow intermediary risk aversion $\gamma_{I,t}$ to proxy for time-varying loadings on

[39] This approach does not rule out richer variation in risk exposure uncorrelated with $\tilde{\gamma}_I$. Rather, it just asks if there is variation in the risk exposure correlated with $\tilde{\gamma}_I$.

pre-specified standard risk factors.[40] Specifically, we estimate

$$r_{i,t+1} = a_i + b_{I,i} \times \tilde{\gamma}_{I,t} + \sum_k (\beta_{0,i,k} + \beta_{1,i,k}\tilde{\gamma}_{I,t}) f_{k,t+1} + \epsilon_{i,t+1}, \tag{19}$$

with a set of returns on K risk factors $f_{k,t+1}, k = 1, ..., K$. If time-varying exposure to these risk factors is not driving our main results, then the inclusion of the interaction $\tilde{\gamma}_{I,t} \times f_{k,t+1}$ (that is, entertaining the possibility that $\beta_{1,i,k} \neq 0$) will not affect the estimates of $b_{I,i}$.[41] In Table IA.XIV, we compare these specifications for various sets of factors added to our baseline. In addition to the market and the liquidity factor, we include the value and size factors of Fama and French (1993), the momentum factor, and the short-term reversal factor, which has been argued to proxy for liquidity provision (Nagel (2012)). While the connection between these factors and specific sources of economic risk is not always well established, they have been used extensively in the reduced-form literature to capture variation in expected returns. We find that none of these specifications meaningfully affect the coefficients $b_{i,I}$ and, in particular, the cross-sectional slope across regression coefficients moves very little across specifications. Taken together, these results do not support an increasing pattern of predictive coefficients based on time-varying quantities of risk.

Finally, controlling for ex-ante (rather than ex-post) measures of risks in the predictive regressions has little effect on the results. Specifically, we

[40] See also Kelly, Pruitt, and Su (2019).

[41] Including the factors could affect $b_{i,I}$ within our model if they capture a sizable fraction of shocks to returns.

construct time-varying volatilities and market betas using rolling five-year regressions for each asset class and include them in the predictive regressions. Table IA.XV reports the estimates. The pattern in coefficients on intermediary health is similar to before, and if anything slightly stronger and more significant due to the additional controls. Figure IA.12, which plots the predictive coefficients and elasticities, confirms this result visually.

Taken together, these results suggest that fluctuations in the quantity of risk do not drive out the role of intermediary health. We acknowledge that a time-varying risk story can never be completely ruled out, for example, if risk is captured by some other unobserved time-varying covariances that we cannot measure. However, across a large variety of typical risk measures we find no evidence that time-varying risk goes in the right direction to qualitatively explain our results.

B. Evidence from Hedge Fund Returns

As an alternative to comparing predictability by intermediary health across asset classes, we compare the properties of more or less complex strategies. We use indices of hedge fund returns from Dow Jones Credit Suisse (DJCS). Hedge fund returns are the returns of specialized strategies and asset classes. We argue that they should respond more to intermediary health than other assets, more so for more complex strategies. We run our predictive regressions again with stocks on the left of our ranking and various hedge fund return strategies on the right. We consider long-short equity funds, market-neutral equity funds, an overall hedge fund index from DJCS of all funds, event-driven funds, convertible bond arbitrage funds, and fixed income arbitrage funds. While we acknowledge that a detailed ranking of strategies as we pursue earlier across asset classes is not available, we use guidance from previous literature on the complexity of these strategies and the degree of sophisticated intermediaries involved in each. We argue that equity strategies are likely more accessible to households. For example, some quant strategies in equities like value and momentum could be implemented by households, although likely at higher costs. In contrast, convertible bond arbitrage and fixed income arbitrage are likely the most difficult for households to engage in. Indeed, intermediary capital effects have been argued to play an important role in both of these strategies. Mitchell and Pulvino (2012) state that hedge funds and arbitrageurs make up 75% of the convertible bond market and document significant dislocations in prices following hedge fund redemptions. Hu, Pan, and Wang (2013) suggest that intermediary capital effects lead to deviations in fixed income along the yield curve. Duarte, Longstaff, and Yu (2007) study specialized fixed income arbitrage pursued by hedge funds, arguing that these strategies require significant intellectual capital and leverage. Event-driven strategies (e.g., merger arbitrage) likely fit in the middle and also exhibit price pressure effects (Mitchell, Pulvino, and Stafford (2004)), as does the index of all hedge funds, which is weighted by AUM under each asset class.

Figure 10 and Table IA.XVI present our results. We find that predictability is higher for all hedge fund strategies compared to stocks, consistent with our main hypothesis that these constitute more specialized strategies that households would have difficulty investing in. Within hedge fund strategies, we also find that convertible bond arbitrage, fixed income arbitrage, and event-driven strategies respond more to intermediary health. Interestingly, the magnitude of predictive coefficients normalized by volatility for more specialized strategies is comparable to that of the more sophisticated asset classes of our main sample. Overall, the results are consistent with the idea that these strategies are more complex and specialized. Moreover, the results further support the view that intermediaries matter using separate data on returns than in our main analysis and as a result strengthen our conclusions.

[**Insert Figure 10 about here.**]

V. Discussion and Relation to Literature

Having documented our main results, it is useful to contrast our approach with existing work on intermediary asset pricing. We find this discussion more useful ex-post, so that we can relate particular aspects of both our empirical work and our model to the literature.

A. Contrast with the Euler Equation Approach

A classic approach to studying households' optimization in financial markets is to examine whether their Euler equation holds. This corresponds to investigating whether households' marginal utility is a stochastic discount factor that can price the cross-section of expected returns. A natural counterpart to this approach, for a view on whether intermediaries are central to asset pricing, is to ask whether intermediaries' Euler equation also holds.

Several papers empirically evaluate the intermediary Euler equation. For instance, Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) construct empirical counterparts of intermediaries' marginal utility and find empirical success in using these variables to explain the cross-section of expected returns.

In our setting, intermediaries have frictionless access to the risky asset market and therefore their Euler equation always holds. Indeed, the portfolio of intermediaries is always mean-variance efficient — see equation (7) – which implies that their marginal utility is a valid pricing kernel for all assets. However, in our model this is true independent of whether intermediaries matter for asset prices. The empirical success of the intermediary Euler equation, while very useful, only validates the specification of a frictionless demand function for intermediaries.

Tests of the household Euler equation can complement this evidence. In our setting, intermediaries matter if and only if the household Euler equation fails. This is a direct consequence of the observation that when intermediaries do not matter, prices coincide with the frictionless benchmark. Specifically, in our model the capital asset pricing model (CAPM) does not hold unless $\left(\Sigma + \frac{1}{\gamma_I}\Sigma_{diag}C\right)^{-1}\left(\Sigma + \frac{1}{\gamma_H}\Sigma_{diag}C\right)$ is the identity matrix.

Since Hansen and Singleton (1983), a long literature has provided evidence inconsistent with particular specifications of the Euler equation for households. It remains unclear whether this empirical failure reflects the fact that the household Euler equation does not hold, whether we have insufficient models of household marginal utility, or whether data on quantities like aggregate consumption are poor for these purposes. For example, Greenwald, Lettau, and Ludvigson (2016) argue that movements in aggregate risk aversion appear to be uncorrelated with standard measures of consumption. Malloy, Moskowitz, and Vissing-Jorgensen (2009) argue that stockholder consumption lines up better with asset returns, while Constantinides and Duffie (1996) and Schmidt (2016) focus on household heterogeneity and idiosyncratic risk. Savov (2011) and Kroencke (2017) argue that measurement of National Income and Product Accounts (NIPA) consumption plays a role in the failure of the consumption-based CAPM (CCAPM). These papers point to failures of the CCAPM for reasons related to preferences or measurement. The approach of this paper is to go beyond these shortcomings and instead discuss predictions of the theory more directly focused on intermediaries.

B. Micro Evidence

Our results also relate to "micro" studies showing that intermediary frictions matter for a particular asset class or at a particular point in time. For example, Siriwardane (2019) documents price dispersion in CDS contracts that relates to dealer net worth — losses for a particular dealer on other contracts affect the CDS price that that dealer is willing to offer, that is, affect their risk-bearing capacity. Similarly, Du, Tepper, and Verdelhan (2018) document that end-of-quarter regulatory constraints for banks affect their risk-bearing capacity and spill over into FX markets. These end-of-quarter constraints result in large violations of covered interest parity for short periods of time. Gabaix, Krishnamurthy, and Vigneron (2007) provide evidence that banks are marginal investors in MBS. Duffie (2010) and He and Krishnamurthy (2018) provide a variety of similar examples.[42] These studies are extremely useful in documenting clean effects of intermediaries on asset prices, by getting as directly as possible to the mechanisms behind intermediary decisions. However, a limitation is that they study specific relative price effects at particular points in time but do not give a sense of more aggregate effects of intermediaries. In particular, it could be the cases that the local disruptions they document "wash out" in the aggregate. By zooming out at a very aggregate level, we get directly at broad asset class variation in risk premia.

The natural next step is to relate magnitudes of intermediary effects in the microeconomic studies with those in the aggregate evidence. To do so, one has to step out of our simple, single-intermediary framework and account for the structure of the intermediary sector. In Internet Appendix Section I.E, we extend the model of Section I.B in the main text to a richer organization of the intermediary sector. Using this setting, one can consider both broad shocks to the entire intermediary sector or shocks specific to a single intermediary and examine the determinants of the price response they imply. However, we also show that doing so relies crucially on quantifying specific properties of the intermediation sector. One must measure the degree of substitutability across intermediaries and the assets they specialize in.[43] For example, to aggregate the results of Siriwardane (2019), one needs to know how easy it is for another dealer to access the same CDS contract and how closely related

[42]See also Lou, Yan, and Zhang (2013).

[43]Morelli, Ottonello, and Perez (2021) is an example of using such an exercise in the context of emerging market debt.

the risks of various CDS contracts are. In addition, one needs to be able to relate the shocks used in various empirical settings to common measures of risk appetite. Doing so is beyond the scope of this paper, and thus we leave this promising avenue open for future research.

VI. Conclusion

A sufficient condition for intermediaries to matter for asset prices is that the risk premium of more intermediated assets responds relatively more to changes in intermediary risk appetite. This prediction is valid even if intermediary risk appetite is positively correlated with other aggregate drivers of risk appetite. We provide direct empirical evidence of this pattern of variation in risk premia. In particular, we argue that intermediaries matter for a number of key asset classes, including CDS, FX, MBS, and commodities. Quantitatively, a sizable amount of the variation in risk premia for these asset classes can be attributed to intermediaries. We view this study as a first step in quantifying the effect of intermediaries on variation in aggregate asset prices.

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Table I
Summary Statistics of Asset Returns

This table reports means, standard deviations, and Sharpe ratios of excess returns for each of the asset classes. All numbers are quarterly. The text describes the returns and sources in detail.

	Stocks (1)	Treas. (2)	Options (3)	Sov. (4)	Comm. (5)	FX (6)	MBS (7)	Credit (8)
$E[r_t]$	1.50%	0.46%	2.35%	1.97%	1.29%	2.06%	0.09%	0.28%
$\sigma(r_t)$	9.10%	1.91%	4.78%	5.39%	6.28%	5.04%	0.68%	1.31%
$E[r_t]/\sigma(r_t)$	0.17	0.24	0.49	0.37	0.21	0.41	0.13	0.22
Observations	167	160	103	65	105	116	97	47

Table II
Ranking of Asset Classes

This table reports rankings by degree of intermediation by source, with our chosen ranking on the top row. From left to right: less intermediated asset classes, with relatively easier access of investing by households, to more intermediated asset classes, with lower participation by households. Sources for the rankings are: Flow of Funds (FoF), BIS derivatives positions, Vale-at-Risk (VaR), and ETF expense ratios. The text explains these sources and rankings in detail.

Our Ranking	Stocks	Treas.	Options	Sov Bonds	Comm	FX	MBS	CDS
FoF	Stocks	Treas.		Sov Bonds			MBS	
VaR	Stocks	Treas.			Comm	FX		
BIS		Treas.	Options		Comm	FX		CDS
Expense	Stocks	Treas.	Sov Bonds	FX	Comm	Options	MBS	CDS

Table III
Intermediary Health and Excess Returns

This table reports results of predictive regressions of future excess returns in each asset class on our proxy for intermediary risk aversion, $\tilde{\gamma}_{I,t}$. We run $r^{\sigma}_{i,t+1} = a_i + b_i \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}$ and report b_i. Excess returns $r^{\sigma}_{i,t+1}$ are normalized by their full-sample volatility. $\tilde{\gamma}_{I,t}$ is the standardized average of the AEM and HKM intermediary factors. Standard errors are computed using the reverse-regression approach of Hodrick (1992). *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, where p-values are computed using the bootstrap approach described in Section III.A. The last row computes the elasticity of expected returns, $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more details.

	Stocks	Treas.	Options	Sov.	Comm.	FX	MBS	Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ_I	0.12	-0.01	0.29***	0.38**	0.18*	0.18*	0.30**	0.57***
	(0.09)	(0.07)	(0.10)	(0.17)	(0.10)	(0.09)	(0.13)	(0.22)
Boots. p-value	0.198	0.904	0.005	0.019	0.083	0.056	0.016	0.006
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.008	-0.006	0.075	0.126	0.022	0.021	0.078	0.316
Elasticity	0.71	-0.04	0.58	1.03	0.87	0.43	2.34	2.67

Table IV
Including Household Risk Aversion

This tables presents results of predictive regressions of future excess returns in each asset class on our proxy for intermediary risk aversion, $\tilde{\gamma}_{I,t}$, and household risk aversion, $\tilde{\gamma}_{H,t}$. We run $r^{\sigma}_{i,t+1} = a_i + b_{I,i} \times \tilde{\gamma}_{I,t} + b_{H,i} \times \tilde{\gamma}_{H,t} + \epsilon_{i,t+1}$ and report b_i. Excess returns $r^{\sigma}_{i,t+1}$ are normalized by their full-sample volatility. $\tilde{\gamma}_{I,t}$ is the standardized average of the AEM and HKM intermediary factors. $\tilde{\gamma}_{H,t}$ is proxied by the consumption wealth ratio (cay) of Lettau and Ludvigson (2001). Standard errors are computed using the reverse-regression approach of Hodrick (1992). *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, where p-values are computed using the bootstrap approach described in Section III.A. The last row computes the elasticity of expected returns, $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	Stocks	Treas.	Options	Sov.	Comm.	FX	MBS	Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ_I	0.15*	-0.00	0.29***	0.36**	0.18*	0.18*	0.31**	0.59**
	(0.09)	(0.07)	(0.10)	(0.17)	(0.10)	(0.09)	(0.13)	(0.27)
γ_H^{cay}	0.21***	0.06	0.12	0.22	0.01	0.12	0.20*	-0.06
	(0.07)	(0.07)	(0.12)	(0.14)	(0.12)	(0.11)	(0.11)	(0.34)
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.044	-0.009	0.075	0.144	0.013	0.022	0.092	0.302
Elasticity								
γ_I	0.91	-0.02	0.58	1.00	0.87	0.43	2.39	2.74
γ_H^{cay}	1.23	0.25	0.24	0.59	0.05	0.29	1.53	-0.26

Table V
Predicting Risk with Intermediary Risk Aversion

This tables presents results of predictive regressions of future risk measures in each asset class on our proxy for intermediary risk aversion, $\tilde{\gamma}_{I,t}$. We run $Y_{i,t+1} = a_i + b_{I,i} \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}$ and report $b_{I,i}$. Excess returns $r_{i,t+1}$ are normalized by their full-sample volatility. Panel A predicts the square returns, $Y_{i,t+1} = r^2_{i,t+1}$. Panel B predicts the exposure to market returns, $Y_{i,t+1} = r_{i,t+1} \times r_{MKT,t+1}$. Panel C predicts the exposure to the liquidity factor of Pástor and Stambaugh (2003), $Y_{i,t+1} = r_{i,t+1} \times r_{LIQ,t+1}$. Standard errors are computed using the reverse-regression approach of Hodrick (1992). *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, where p-values are computed using the bootstrap approach described in Section III.A.

	Stocks (1)	Treas. (2)	Options (3)	Sov. (4)	Comm. (5)	FX (6)	MBS (7)	Credit (8)
Panel A. Variance ($r^2_{i,t+1}$)								
γ_I	0.34**	0.17	0.10	0.23	0.30	-0.09	0.15	0.35
	(0.16)	(0.13)	(0.17)	(0.34)	(0.26)	(0.11)	(0.20)	(0.54)
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.041	-0.002	-0.007	-0.005	0.004	-0.004	-0.004	-0.000
Panel B. Market Risk Exposure ($r_{i,t+1} \times r_{MKT,t+1}$)								
γ_I	0.38**	0.07	0.27*	0.24	0.09	0.14	0.11	0.22
	(0.16)	(0.08)	(0.14)	(0.28)	(0.11)	(0.12)	(0.17)	(0.39)
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.057	-0.003	0.046	0.009	-0.004	0.006	-0.003	-0.005
Panel C. Liquidity Risk Exposure ($r_{i,t+1} \times r_{LIQ,t+1}$)								
γ_I	0.07	-0.03	0.27**	0.06	0.14	0.04	0.13	0.00
	(0.14)	(0.06)	(0.14)	(0.14)	(0.18)	(0.10)	(0.16)	(0.27)
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	-0.004	-0.006	0.026	-0.013	-0.004	-0.008	-0.002	-0.022

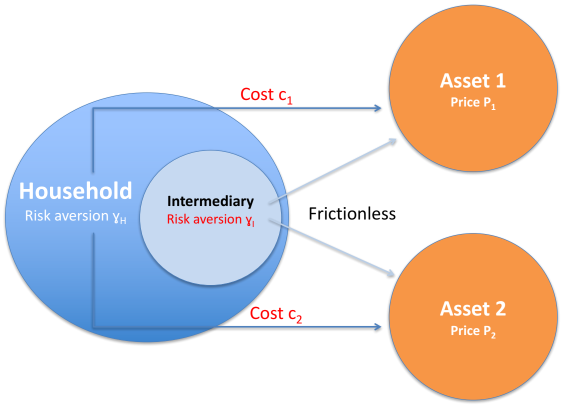
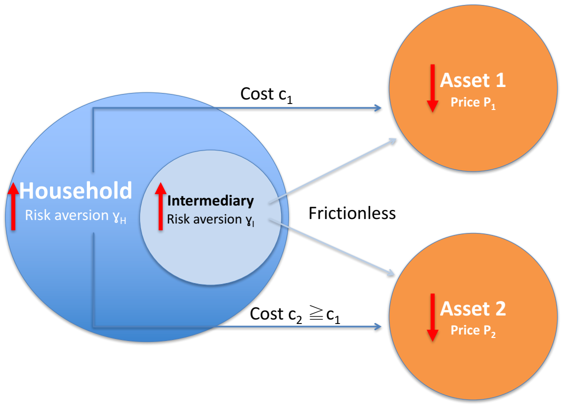


Figure 1. Model setting. This figure illustrates the model with two risky assets, but it can be easily generalized to N assets. We highlight that the household owns the intermediary in the model (though they may have differing risk aversions) and the household can invest directly in various assets at different costs c_1, c_2, with the costs higher in some assets (e.g., CDS markets) than others (e.g., the stock market).

Panel A. Response to aggregate risk aversion shock under null



Panel B. Response to intermediary risk aversion shock

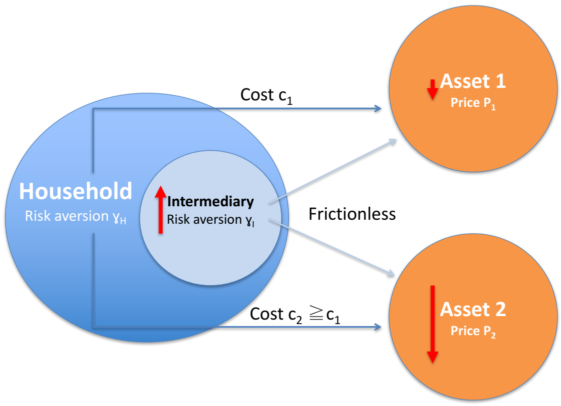


Figure 2. Model shocks. This figure illustrates the response of asset prices to changes in risk aversion. In Panel A, we show the response of a risk aversion shock under the null that intermediaries do not matter (because $c = 0$ for all assets or because $\gamma_I = \gamma_H$) and hence all risk premia move proportionally when risk aversion changes. In Panel B, we show the response of an intermediary risk aversion shock in the case in which there are differential costs c across assets and hence differential risk premium responses.

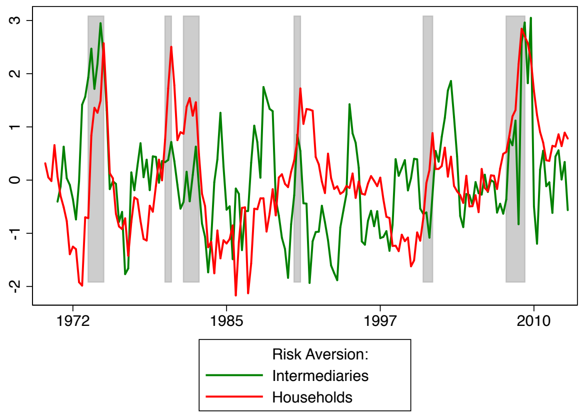


Figure 3. Intermediary and household risk aversion. This figure plots our proxy for intermediary risk aversion taken from AEM and HKM (green). For reference, we also plot the aggregate risk aversion implied by a habit model using aggregate consumption (red).

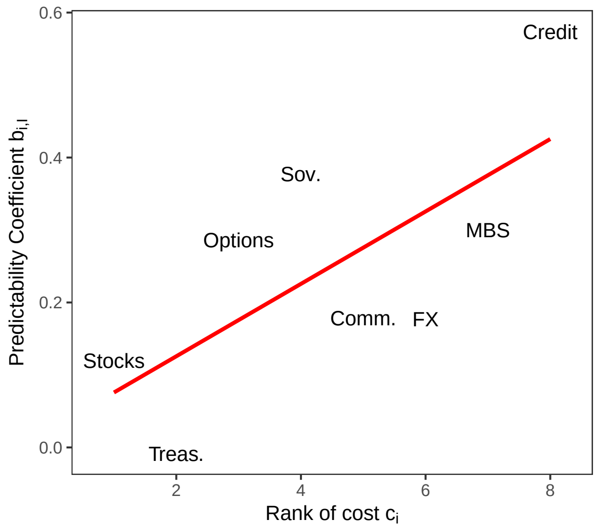


Figure 4. Predictability across asset classes: Predictive coefficients. This figure plots the predictive coefficients from Table III, which runs predictive regressions of excess returns on intermediary effective risk aversion. The x-axis is our ranking for how intermediated each asset class is. The red line is a linear regression fit through these points. An upward slope indicates more predictability in more intermediated asset classes.

Panel A. Elasticity

Panel B. R^2

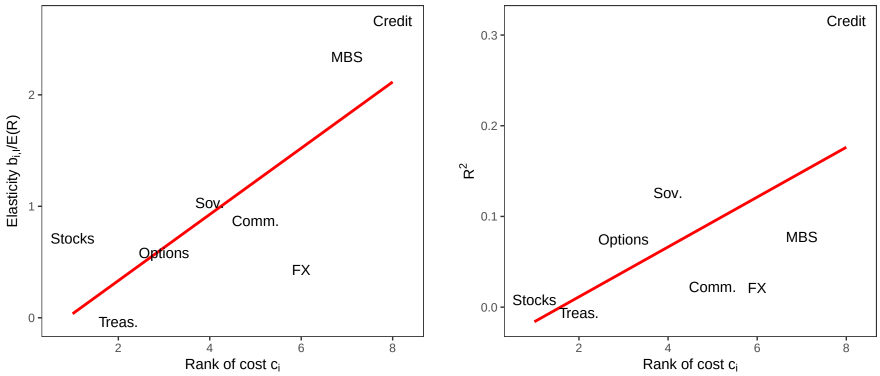


Figure 5. Predictability across asset classes: Risk premium elasticity and R^2. Panel A repeats the previous figure using the elasticity of the risk premium to intermediary risk aversion: the predictive coefficient divided by the sample mean of excess returns in each asset class. Panel B measures the degree of predictability using the R^2 in each predictive regression across asset classes (see Table III). The x-axis is our ranking for how intermediated each asset class is. The red line is a linear regression fit through these points. An upward slope indicates more predictability in more intermediated asset classes.

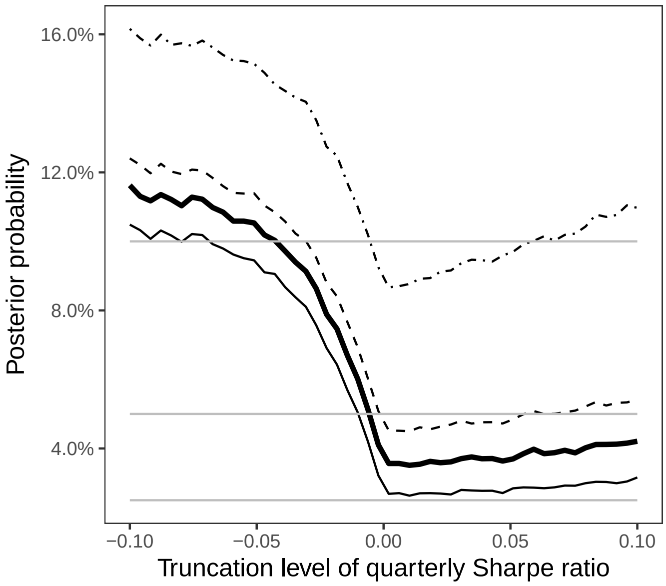


Figure 6. Posterior probability of less predictability for intermediated asset classes: The effect of truncation. This figure plots the posterior probability that the elasticity of the risk premium to intermediary health is lower for more intermediated assets. The x-axis varies the lower bound on the prior of the unconditional quarterly Sharpe ratio. The different lines correspond to different criteria for less predictability. The thick black line corresponds to the slope of a linear regression across elasticities. The thin black line compares the average elasticity of Credit and MBS to the average elasticity of Stocks and Treasuries. The dotted-dash line compares Stocks and Treasuries to all other asset classes. The dotted line compares Stocks, Treasuries, and Options to all other asset classes.

Panel A. Slope across asset classes

Panel B. Probability of less predictability for intermediated assets

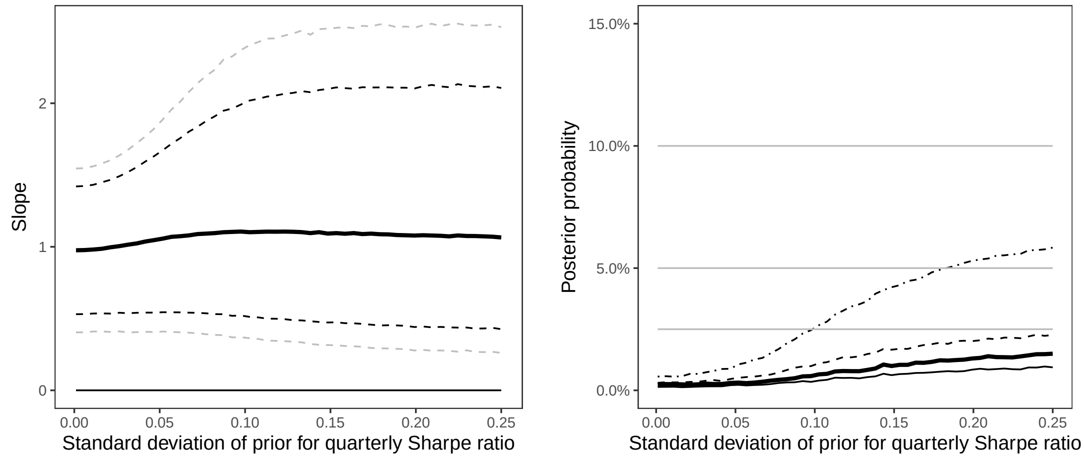


Figure 7. Statistical significance of predictability across asset classes. The x-axis varies the standard deviation on the prior of the unconditional quarterly Sharpe ratio; lower values imply a shrinkage towards the assumption of a constant unconditional Sharpe ratio across asset classes equal to 0.25. Panel A plots the distribution of the slope of a linear regression across elasticities: median, 5th, 10th, 90th, and 95th percentile. Panel B plots the posterior probability that the elasticity of the risk premium to intermediary health is lower for more intermediated assets. The different lines correspond to different criteria for less predictability. The thick black line corresponds to the slope of a linear regression across elasticities. The thin black line compares the average elasticity of Credit and MBS to the average elasticity of Stocks and Treasuries. The dotted-dash line compares Stocks and Treasuries to all other asset classes. The dotted line compares Stocks, Treasuries, and Options to all other asset classes.

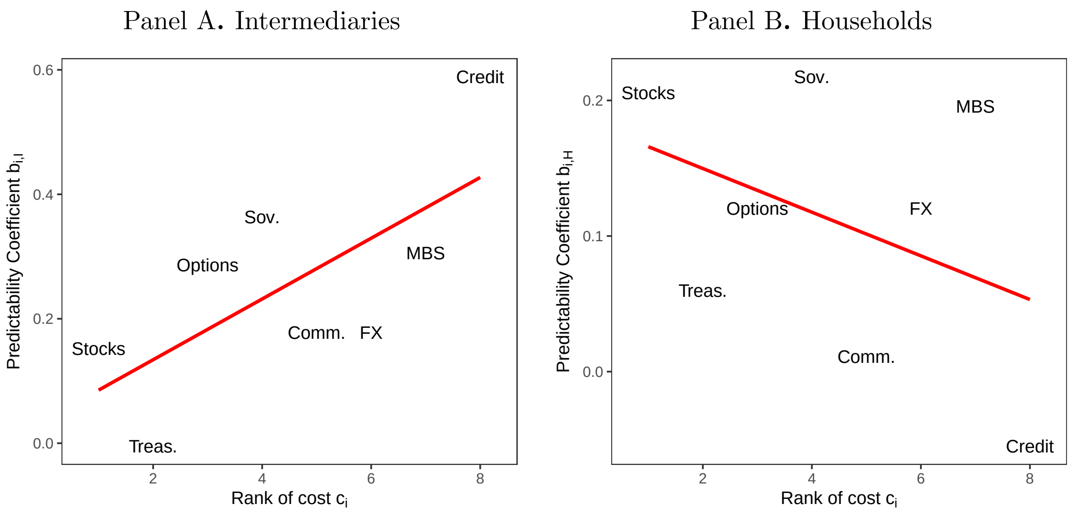


Figure 8. Predictability across asset classes: Households versus intermediaries. This figure plots coefficients from a predictive regression of excess returns on intermediary effective risk aversion and household risk aversion, as proxied by the consumption-wealth ratio. The x-axis is our ranking for how intermediated each asset class is. Panel A shows the coefficient pattern for intermediary risk aversion, and Panel B for household risk aversion. The red line is a linear regression fit through these points. An upward slope indicates more predictability in more intermediated asset classes, and vice versa. See text for more details.

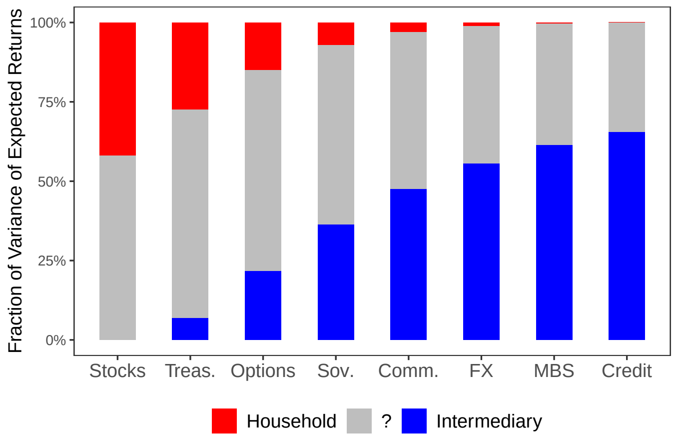


Figure 9. Decomposition of risk premium variation. This figure shows lower bounds of variation in risk premia coming from households and intermediaries for each asset class using the pattern of predictability across asset classes. See text for more details.

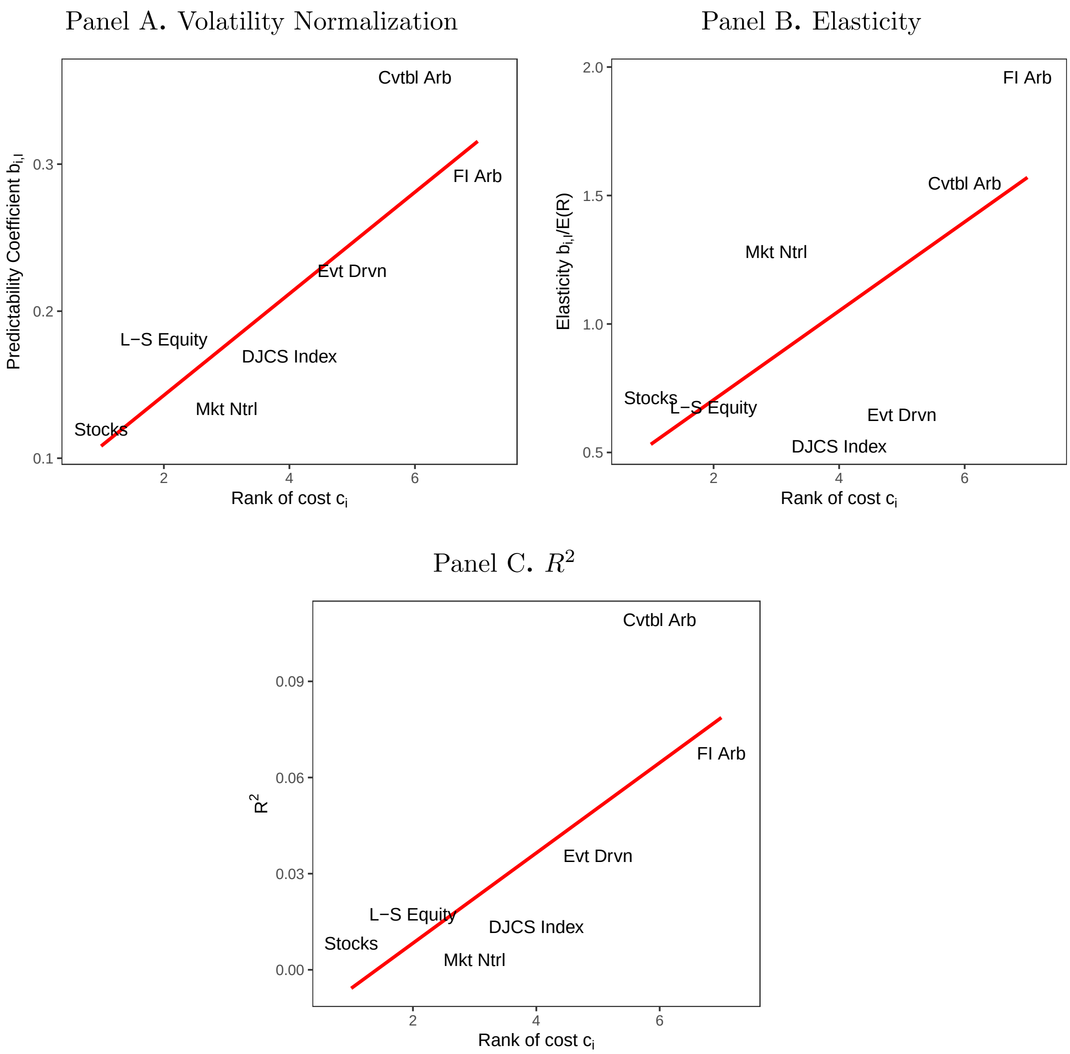


Figure 10. Hedge fund strategy returns. This figure shows the behavior of risk premiums across stocks and hedge fund returns by category: long-short equity, market-neutral equity, the DJCS hedge fund index weighted across all hedge fund styles, event driven, convertible bond arbitrage, and fixed income arbitrage. Panel A runs $r^{\sigma}_{i,t+1} = a_i + b_i \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}$ and plots b_i across fund categories. Excess returns $r^{\sigma}_{i,t+1}$ are normalized by their full-sample volatility. Panel B plots the risk premia elasticity found by running $r_{i,t+k}/E[r_{i,t+k}] = a_i + b_i\tilde{\gamma}_{I,t} + \varepsilon_{i,t+k}$. The right-hand side variable $\gamma_{I,t}$ that captures intermediary health is an equal-weighted average of the AEM and HKM factors. Panel C plots the R^2 in this predictive regression. See text for more details.