Internet Appendix for
"Do Intermediaries Matter for Aggregate Asset Prices?"

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ABSTRACT

This Internet Appendix provides formal derivations of our results as well as additional evidence supporting the main text.

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IA.I. Discussion of the Test and Model

A. Formal Derivation of the Bound on Risk Premium

We write down the formal argument behind the test introduced in Section I.A. Specifically, we show that, under the assumptions we make about the determination of risk premium, an increasing pattern of predictive coefficients on a proxy for intermediary risk aversion reveals that intermediary health matters for risk premia. Second, we show how the magnitude of the increase in predictability yields a lower bound for the variance in risk premium due to intermediaries.

1. Assumptions

Repeating the setup of Section I.A, we have:

$$\tilde{r}_{i,t+1} = a_i + \beta_{i,H}\gamma_{H,t} + \beta_{i,I}\gamma_{I,t} + \varepsilon_{i,t+1}, \tag{IA1}$$

with $\varepsilon_{i,t+1}$ uncorrelated with time t information.

Our first assumption is that expected returns are non-decreasing in intermediary or household risk aversion, that is $\beta_{i,H} \geq 0$ and $\beta_{i,I} \geq 0$ for all i.

Second, we assume that assets that are more difficult to access directly have a risk premium that responds more to indermediary risk aversion, and less or equal to household risk aversion. If, without loss of generality, the assets are ranked from lowest to highest cost or access, this corresponds to:

$$\beta_{i,H} \geq \beta_{i',H}, \ \forall i < i', \tag{IA2}$$

$$\beta_{i,I} \leq \beta_{i',H}, \ \forall i < i'. \tag{IA3}$$

Finally, we have a proxy for intermediary risk aversion $\hat{\gamma}_{I,t}$. This proxy satisfies $cov\left(\hat{\gamma}_{I,t}, \gamma_{I,t}\right) > 0$ and $cov\left(\hat{\gamma}_{I,t}, \gamma_{H,t}\right) \geq 0$. These conditions allow $\hat{\gamma}_{I,t}$ to also load on other irrelevant factors. We define $b_{i,I}$ as the coefficient of a predictive regression using $\tilde{\gamma}_{I,t}$:

$$\tilde{r}_{i,t+1} = a_i + b_i \tilde{\gamma}_{I,t}. \tag{IA4}$$

2. Results

Let us compare the predictive coefficient on an arbitrary asset i with the lowest cost asset 1. Naturally all this reasoning also holds with replacing asset 1 by any asset $i' < i$. We obtain:

$$\begin{aligned} b_i - b_1 &= \frac{cov\left(\tilde{r}_{i,t+1} - \tilde{r}_{1,t+1}, \tilde{\gamma}_{I,t}\right)}{var\left(\tilde{\gamma}_{I,t}\right)} && \text{(IA5)} \\ &= \frac{cov\left(\left(\beta_{i,H} - \beta_{1,H}\right)\gamma_{H,t} + \left(\beta_{i,I} - \beta_{1,I}\right)\gamma_{I,t} + \varepsilon_{i,t+1}, \tilde{\gamma}_{I,t}\right)}{var\left(\tilde{\gamma}_{I,t}\right)} && \text{(IA6)} \\ &= \frac{\left(\beta_{i,H} - \beta_{1,H}\right) cov\left(\gamma_{H,t}, \tilde{\gamma}_{I,t}\right) + \left(\beta_{i,I} - \beta_{1,I}\right) cov\left(\gamma_{I,t}\tilde{\gamma}_{I,t}\right)}{var\left(\tilde{\gamma}_{I,t}\right)}. && \text{(IA7)} \end{aligned}$$

Because $\left(\beta_{i,H} - \beta_{1,H}\right) \leq 0$ and $cov\left(\gamma_{H,t}, \tilde{\gamma}_{I,t}\right) \geq 0$, we have immediately:

$$b_i - b_1 \leq \frac{\left(\beta_{i,I} - \beta_{1,I}\right) cov\left(\gamma_{I,t}\tilde{\gamma}_{I,t}\right)}{var\left(\tilde{\gamma}_{I,t}\right)}. \tag{IA8}$$

This is our first result. Note that the covariance on the right-hand-side is positive, and $\beta_{1,I}$ is nonnegative. Hence, intermediary health matters for asset i, that is $\beta_{i,I} > 0$, if asset i is more positively predicted by the proxy than asset 1, $b_i - b_1 > 0$.

Assuming this comparison holds, we have:

$$(b_i - b_1)^2 \, var\left(\tilde{\gamma}_{I,t}\right) \leq \left(\beta_{i,I} - \beta_{1,I}\right)^2 \frac{cov\left(\gamma_{I,t}\tilde{\gamma}_{I,t}\right)^2}{var\left(\tilde{\gamma}_{I,t}\right)}. \tag{IA9}$$

Using the Cauchy-Schwarz inegality, this relation becomes:

$$(b_i - b_1)^2 \, var\left(\tilde{\gamma}_{I,t}\right) \leq \left(\beta_{i,I} - \beta_{1,I}\right)^2 var\left(\gamma_{I,t}\right). \tag{IA10}$$

Finally, using the fact that $\beta_{i',I}$ is nondecreasing in i' and nonnegative, we obtain immediately:

$$(b_i - b_1)^2 \, var\left(\tilde{\gamma}_{I,t}\right) \leq \beta_{i,I}^2 var\left(\gamma_{I,t}\right). \tag{IA11}$$

This is our second result. The left-hand-side of this inequality, obtained only from regressions using the proxy therefore constitutes a lower bound for the variance in risk premium coming from intermediary risk aversion, the right-hand-side.

Of course, one can use a symmetric argument with a proxy for household risk aversion if it generates a decreasing pattern of predictive coefficients.

B. Elasticity Arithmetic

We discuss a few mechanical properties of the elasticity of risk premium we measure empirically. If we run the regression

$$r_{i,t+1} = a_i + b_i \tilde{\gamma}_{I,t} + \varepsilon_{i,t+1}, \tag{IA12}$$

the risk premium elasticity $\mathcal{E}_i$ is defined as the ratio of the predictive coefficient to the unconditional average return $\mathcal{E}_i = b_i / \mathbb{E}[r_{i,t+1}]$.

Scaling. If we lever up an excess return, the elasticity is unchanged. For example, assume $r_{j,t+1} = \lambda r_{i,t+1}$ for all t. Then, we have $b_j = \lambda b_i$ and $\mathbb{E}[r_{j,t+1}] = \lambda \mathbb{E}[r_{i,t+1}]$. Therefore the ratio is unchanged.

Idiosyncratic risk. Adding idiosyncratic risk to an excess return leaves the elasticity unchanged. This corresponds to a situation with $r_{j,t+1} = r_{i,t+1} + u_{t+1}$ with $\mathbb{E}_t[u_{t+1}] = 0$ for all t. Then clearly neither the predictive coefficient nor the unconditional returns are affected.

Combining elasticities. When adding two returns, the resulting elasticity is the average of the each return's elasticity, weighted by their contribution to the expected return of the portfolio. Assume that $r_{k,t+1} = r_{i,t+1} + r_{j,t+1}$. Then $\mathbb{E}[r_{k,t+1}] = \mathbb{E}[r_{i,t+1}] + \mathbb{E}[r_{j,t+1}]$ and $b_k = b_i + b_j$. So we have:

$$\mathcal{E}_k = \frac{b_i + b_j}{\mathbb{E}[r_{i,t+1}] + \mathbb{E}[r_{j,t+1}]} \tag{IA13}$$

$$= \frac{\mathbb{E}[r_{i,t+1}]}{\mathbb{E}[r_{i,t+1}] + \mathbb{E}[r_{j,t+1}]}\mathcal{E}_i + \frac{\mathbb{E}[r_{j,t+1}]}{\mathbb{E}[r_{i,t+1}] + \mathbb{E}[r_{j,t+1}]}\mathcal{E}_j. \tag{IA14}$$

C. Basic Price-Theoretic Analysis

We generalize the results in the main text by introducing the simplest price-theoretic framework of an asset market that includes an intermediary. This setting highlights the two basic forces determining the role of intermediaries for asset prices. The first element is their demand for the asset, how they make investment decisions. The second element is how final investors substitute between holding the assets through the intermediary and directly. We then flesh out a particular model that fits this framework before discussing alternative foundations for those two key elements.

Consider the market for one asset, in supply S, that will trade in equilibrium at price p.[†] The asset is characterized by a vector of attributes x_A, e.g. the mean and variance of its final payoff. There are two market participants, households, and intermediaries.

Intermediaries are characterized by a vector of attributes x_I, e.g. their size, leverage, or manager. Their demand for the asset depends on the characteristics of the asset x_A, their own attributes x_I, and the price of the asset p, summarized by the function $D_I(p, x_A, x_I)$.

Households are characterized by a vector of attributes x_H, e.g. their wealth, risk aversion, or beliefs. Importantly they own the intermediaries. Therefore, their demand for the asset depends not only on the price, their attributes and the attributes of the asset, but also of how much of the asset they is owned by the intermediary D_I^*. This is summarized by the function

[†]The case of a non-fixed supply function, for instance $S(p)$ does not affect our conclusions.

$D_H(p, D_I^*, x_A, x_H)$.

These demand functions map to the notation of our setting in the main text. The attributes of the assets are μ, σ and c. The attributes of the household and the intermediary are γ_H and γ_I respectively. The intermediary chooses the standard mean variance optimal, the ratio of the expected return $\mu - p$ to the product of payoff variance σ^2 and its risk aversion σ^2. The households targets a similar optimum total portfolio, but offsets her own trading to take into account the assets she already holds through the intermediary. The inside-outside substitution rate is $-\partial D_H / \partial D_I = \frac{\gamma_H \sigma^2}{\gamma_H \sigma^2 + c}$. Finally, there will be a difference in preferences (and hence a separate notion of intermediary demand), when $\gamma_I \neq \gamma_H$. The case where they are equal essentially means the intermediary simply acts on the households behalf with no friction.

The equilibrium price is determined by market clearing, plugging into households demand the intermediary demand for the asset:

$$D_H\left(p, D_I(p, x_A, x_I), x_A, x_H\right) + D_I(p, x_A, x_I) = S \tag{IA15}$$

To understand price determination, consider the local change in price in response to a change in the various attributes:

$$\Delta p = \underbrace{\frac{-1}{\frac{\partial D_H}{\partial p} + \left(1 + \frac{\partial D_H}{\partial D_I}\right)\frac{\partial D_I}{\partial p}}}_{\text{demand slope}}$$
$$\times \left[\underbrace{\left(\frac{\partial D_H}{\partial x_A} + \left(1 + \frac{\partial D_H}{\partial D_I}\right) \frac{\partial D_I}{\partial x_A} \right) \Delta x_A}_{\text{asset attributes}} + \underbrace{\frac{\partial D_H}{\partial x_H}\Delta x_H + \left(1 + \frac{\partial D_H}{\partial D_I}\right) \frac{\partial D_I}{\partial x_I}\Delta x_I}_{\text{investor attributes}} \right] \tag{IA16}$$

The first term in the product is the slope of the aggregate demand curve, the second term is the shift in demand curves coming from a change in the attributes. From this relation, we can immediately see that two ingredients shape the impact of intermediaries on asset prices. The first element is not surprisingly the *intermediary demand* for the asset. In particular, how their investment decisions respond to changes in their environment affects the aggregate demand for the asset, and in equilibrium the price. This effect manifests itself through the partial derivatives of D_I in equation (IA16).

The second element is how households substitute between holdings through the intermediary and direct holdings. This corresponds to what we call the *inside-outside substitution rate*, the sensitivity $-\partial D_H/\partial D_I$. This sensitivity controls the extent to which households offset intermediaries trade by directly trading the asset.

To highlight the separate importance of those two elements, let us consider the particular cases where intermediaries do not affect prices. For our first element, it could be that the investments of intermediary do not have depend at all on their attributes, but rather only on households attributes. In this case there wouldn't be a meaningful notion of intermediary demand curve. Intuitively, this occurs if intermediaries simply reflect the preferences of households and act on their behalf with no friction. For our second element, it might be that households substitute exactly one-to-one between the assets they hold directly and those held through intermediaries, perfectly offsetting these decisions ($-\partial D_H/\partial D_I = 1$). Intuitively, this occurs if households can invest directly in asset markets with no cost and there is no advantage to investing through intermediaries.

D. *Interpretation of the Frictions*

1. Imperfect Substitution

The second ingredient is that households do not offset changes in the decisions of intermediaries through direct investing, $-\partial D_H/\partial D_I \neq I$. A simple motivation for this feature is that it is difficult for households to access some risky asset markets, for instance for some complex financial products. We materialize this force by the cost of direct investing C. Existing models of intermediation such as He and Krishnamurthy (2013) typically assume that households cannot invest at all in risky assets, $C = \infty$. A slightly different version is that there is a discretely lower value to risky assets when in the hands of households, for instance in Brunnermeier and Sannikov (2014). This assumption would also generate no direct investing at all in most of the equilibrium. In contrast, an entirely frictionless view of direct investing, $C = 0$, completely rules out a role for financial intermediaries. A benefit of our smooth parametrization is that it allows to control the difficulty for households to invest in risky assets, and explore its role empirically.

Other reasons can lead to an imperfect substitution of direct investing against intermediated investment. Households might be less able to manage portfolios of risky assets, making them effectively more risky. Eisfeldt et al. (2017) studies a model along these lines. It might also be that households are only imperfectly informed about the trades that intermediaries do, and therefore do not completely undo changes in their balance sheets through direct trading.

2. Intermediary Decisions

The first ingredient is that the intermediaries do not invest in a way that reflects the preferences of households. If this is not the case, intermediaries are just a veil. We represent this distinction by allowing the parameter γ_I to differ from γ_H. In practice, there can be many reasons for why the risk-taking decisions of intermediaries differ from those of households. Managers of financial institutions might have different preferences from their investors and limits to contracting 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 (forthcoming)). The presence of costs of financial distress, combined with a limited ability to raise capital also gives rise to a risk management policy specific to the institution. 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 Value-at-Risk. Adrian and

Shin (2014) explore this channel.

While these justifications explain a mismatch in investment policies at the micro level, the overall supply of intermediation could adjust so that there are just enough intermediaries to satisfy household's investment needs. One reason this would not be the case is that there are barriers to entry into the intermediation industry, or that raising capital to create an intermediary is difficult. Another reason might be that the private incentives of the managers of intermediaries to enter the market are not lined up with aggregate households' incentives. Haddad (2013) presents a model with free entry into intermediation and shows that even under such conditions, variation in intermediation technology or in aggregate uncertainty gives rise to fluctuation in the aggregate risk appetite of the financial sector.

In this paper, we do not take a stand on the precise micro foundations for this distinction in risk appetite. Instead we highlight this feature as being important for intermediaries to matter for asset prices and devise tests to uncover its presence.

E. A Richer Intermediation Sector

In our basic setting, there is only one intermediary, and we consider shocks that affect this intermediary. We show how our framework can entertain richer organizations of the intermediation sector. The goal of this analysis is twofold. First, we show that a common shock to the risk appetite of all intermediaries triggers a similar response to our baseline model. Second, this setting highlights what additional information is necessary in order to relate our aggregate results with micro evidence on shocks affecting specific dealers or sectors.

1. Setup and Equilibrium

We have n risky assets indexed by i with payoffs that have mean μ_i and variance σ_i^2. Each asset has m_i specialized intermediaries indexed by j, that can only invest in asset i. This degree of specialization is the other extreme from the baseline model where intermediaries could invest in all possible assets, in order to highlight the contrast with that baseline. It is straightforward to consider intermediate situations, at the cost of more complex notation. We assume that intermediary (i, j) has absolute risk aversion $\gamma_{i,j}$. Households face the same problem as in the baseline model.

Each intermediary demand is

$$D_{i,j} = \frac{1}{\gamma_{i,j}} \frac{\mu_i - p_i}{\sigma_i^2}. \tag{IA17}$$

The aggregate intermediary demand for asset i is

$$D_{I,i} = \left(\sum_j \frac{1}{\gamma_{i,j}} \right) \frac{\mu_i - p_i}{\sigma_i^2}. \tag{IA18}$$

Household demand is

$$D_{H,i} = \frac{\mu_i - p_i}{(\gamma_H + c_i)\,\sigma_i^2} - \frac{\gamma_H \sigma_i^2}{(\gamma_H + c_i)\,\sigma_i^2} D_{I,i}. \tag{IA19}$$

Finally, the equilibrium expected return of asset i is:

$$\mu_i - p_i = \gamma_H \sigma_i^2 S_i \frac{1 + \frac{1}{\gamma_H} c_i}{1 + \left(\sum_j \frac{1}{\gamma_{i,j}} \right) c_i}. \tag{IA20}$$

We define the total intermediary risk aversion for asset i, $\gamma_{I,i}$ by:

$$\gamma_{I,i} = \left(\sum_j \frac{1}{\gamma_{i,j}} \right)^{-1}, \tag{IA21}$$

and decompose each risk aversion into an aggregate and an idiosyncratic components:

$$\gamma_{i,j} = \gamma_{I,i} \gamma_{i,j}^{idio}. \tag{IA22}$$

2. Aggregate Comparative Statics

First, let us consider the effect of a change in household risk aversion γ_H or in the aggregate intermediary risk aversion $\gamma_{I,i}$, holding the idiosyncratic components unchanged. In this model, we have:

$$\beta_{i,I} = \frac{1}{\mu_i - p_i} \frac{\partial \left(\mu_i - p_i \right)}{\partial log \left(\gamma_{I,i} \right)} = \frac{c_i}{\gamma_{I,i} + c_i}, \tag{IA23}$$

$$\beta_{i,H} = \frac{1}{\mu_i - p_i} \frac{\partial \left(\mu_i - p_i \right)}{\partial log \left(\gamma_H \right)} = \frac{\gamma_H}{\gamma_H + c_i}. \tag{IA24}$$

These two results closely relate to equations (12) and (13) in the model with a single intermediary. The effect of household risk aversion is decreasing in c_i, while the effect of intermediary risk aversion in increasing in c_i. The one difference is that in this setting with segmented intermediaries, sector-specific differences also play a role: the same percentage change in intermediary risk aversion has a bigger impact for assets with low intermediary risk aversion. If $\gamma_{i,I}$ is equal across assets, then we are exactly back to the baseline model.

3. Changes to a Single Intermediary

Consider now the effect of changing $\gamma_{i,j}^{idio}$ for one specific intermediary. In this case, we have an elasticity:

$$\beta_{i,j} = \frac{1}{\mu_i - p_i}\frac{\partial\left(\mu_i - p_i\right)}{\partial log\left(\gamma_{i,j}\right)} = \frac{c_i}{\gamma_{I,i} + c_i} \tag{IA25}$$

$$= \frac{1}{\mu_i - p_i}\frac{\partial\left(\mu_i - p_i\right)}{\partial log\left(\gamma_{i,I}\right)}\frac{\partial log\left(\gamma_{i,I}\right)}{\partial log\left(\gamma_{i,j}\right)} \tag{IA26}$$

$$= \frac{c_i}{\gamma_{I,i} + c_i}\frac{\frac{1}{\gamma_{i,j}}}{\sum_j \frac{1}{\gamma_{i,j}}}. \tag{IA27}$$

The effect of a shock to one intermediary is the product of the effect of an aggregate shock multiplied by the share of total risk tolerance (the inverse of risk aversion) coming from this specific intermediary. In the case with a single intermediary this is obviously the same as an aggregate shock. In the other extreme of many small intermediaries, individual shocks do not affect prices.

It does not imply that we can say the shock is inconsequential, rather it occurs mostly in a change in the portfolio of the afflicted intermediary. The elasticity of equilibrium demand in response to the shock is

$$\frac{\partial log\left(D_{i,j}\right)}{\partial \gamma_{i,j}} = -1 + \beta_{i,j}. \tag{IA28}$$

So, naturally, the lower the overall price effect $\beta_{i,j}$ is, the stronger response of the intermediary in terms of quantity.

4. Relating the Evidence Across Empirical Settings

What do we learn about relating evidence across different empirical settings? First, our simple analytical framework can also make sense of richer situations with more intermediary specialization, and shocks to only a subset of these intermediaries.

Second, it is important to account for the degree of substitutability across intermediaries and markets. The results above show that, if many intermediaries are specialized in an asset, the price response to shocks to a single intermediary will be less pronounced; the quantity response will be larger. Substitutability across intermediaries goes along with substitutability across assets. For example, think of the case where two different intermediaries are each specialized in one of two different assets. If these assets are uncorrelated, then we are back to the model above with one intermediary for each sector. However, if the assets are perfectly correlated, this is equivalent to having the two intermediaries in effectively the same market, each contributing their own risk tolerance.

Finally, another important challenge is that we rarely observe directly shocks in terms of risk aversion of intermediaries. In our aggregate data, we use measures of the overall health of the financial sector as variables related to this risk aversion. In microeconomic settings, researchers construct shocks that affect the ability of individual intermediaries to invest such as changes in net worth or regulatory constraints. While one can learn valuable information by mapping each shock to a response of risk premium, comparing experiments necessitates expressing the shocks in the same units.

IA.II. Value-at-Risk Data

We use data on 17 primary dealers obtained from Bloomberg: JP Morgan, Bank of America, Morgan Stanley, Goldman Sachs, Wells Fargo, Citigroup, Barclays, Credit Suisse, Deutsche Bank, HSBC, BNP Paribas, Societe General, Royal Bank of Canada, Bank of Nova Scotia, Nomura Holdings, UBS, Toronto-Dominion, and Royal Bank of Scotland.

IA.III. Bayesian Approach to Statistical Inference

We present formally our Bayesian setting. Then, we explain how to account for an unbalanced panel. Finally. we discuss the role of volatility uncertainty in the estimation.

A. Estimation Framework

We start from equation (15):

$$r_{i,t+1} = a_i + b_i \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}, \tag{IA29}$$

where $\tilde{\gamma}_{I,t}$ has mean zero. We assume that $\epsilon_{i,t+1}$ are independent across time. Given t, we assume that $(\epsilon_{1,t+1}, \epsilon_{2,t+1}, ..., \epsilon_{N,t+1}) \sim \mathcal{N}(0, \Sigma_\epsilon)$. Finally, we assume that Σ_ϵ is known and $\theta = (a_1, b_1, a_2, b_2, ..., a_N, b_N)'$ is the parameter vector to estimate.

The prior for θ is a multivariate truncated normal. We assume its mean is $\bar{\theta} = \sqrt{diag(\Sigma_\epsilon)} \otimes (0.25, 0)'$ and its variance-covariance matrix is $\Sigma_\theta = \Sigma_\epsilon \otimes diag(\sigma_a^2, \sigma_b^2)$. Finally, we assume that the distribution of Sharpe ratios is truncated at some lower threshold $\underline{a}$ for each series: $a_i \geq \underline{a}\sqrt{\Sigma_{\epsilon,ii}}$, $\forall i = 1, ...N$.

We can define a stacked version of our data. First, for each series, we have:

$$X_i = \begin{pmatrix} 1 & \gamma_{I,1} \\ \vdots & \vdots \\ 1 & \gamma_{I,T} \end{pmatrix}, \tag{IA30}$$

$$Y_i = \begin{pmatrix} r^\sigma_{i,2} \\ \vdots \\ r^\sigma_{i,T+1} \end{pmatrix}, \tag{IA31}$$

$$\epsilon_i = \begin{pmatrix} \epsilon_{i,2} \\ \vdots \\ \epsilon_{i,T+1} \end{pmatrix}. \tag{IA32}$$

Then, we combine them into:

$$X = \begin{pmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & X_N \end{pmatrix}, \tag{IA33}$$

$$Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_N \end{pmatrix}, \tag{IA34}$$

$$\epsilon = \begin{pmatrix} \epsilon_1 \\ \vdots \\ \epsilon_N \end{pmatrix}. \tag{IA35}$$

With these notations, we have $Y = X\theta + \epsilon$, and $\epsilon \sim \mathcal{N}(0, \Sigma_\epsilon \otimes I_T)$.

Denote U the Cholesky decomposition of the matrix Σ_ϵ, which is the triangular solution of $\Sigma = U'U$.[‡] This matrix allows to rotate the data to have orthogonal errors. We define: $\tilde{Y} = \left((U^{-1})' \otimes I_T\right) Y$ and $\tilde{X} = \left((U^{-1})' \otimes I_T\right) Y$.

Then, the posterior for θ is a multivariate truncated normal. The mean and variance parameters are given by $\left(\tilde{X}'\tilde{X} + \Sigma_\theta^{-1}\right)^{-1} \left(\tilde{X}'\tilde{Y} + \Sigma_\theta^{-1}\bar{\theta}\right)$ and $\left(\tilde{X}'\tilde{X} + \Sigma_\theta^{-1}\right)^{-1}$, respectively. The posterior distribution is truncated at the same thresholds as the prior.

We compute other moments of this posterior joint distribution of parameters by simulation. We draw 100,000 times a vector θ from this distribution.

[‡]Naturally, the posterior is the same independently of which solution of $\Sigma = U'U$ is chosen.

Then, for example, we compute the cross-sectional slope of elasticities for each draw. We can then compute objects like the median slope or the probability that the slope is negative.

B. Dealing with the Unbalanced Panel

The time series of returns that we use for the various asset classes span different time periods. Some special care must be taken to implement the formulas above to account for this feature. We do so as follows. First, we estimate each individual regression in its fully available sample and compute the corresponding Σ_ϵ by using complete observations to ensure that the estimate is definite positive. Then, we turn to the rotation of the data to construct $\tilde{X}$ and $\tilde{Y}$. The triangular aspect of U implies that missing observations in the first return series will become missing in all subsequent return series, missing observations in the second return series will become missing in all subsequent return series, ... We order the return series to maximize the number of non-missing observations. To find this permutation, we compute all $8! = 40,320$ orderings of the data and choose the optimal one. Then, we just remove all rows from $\tilde{X}$ and $\tilde{Y}$ which feature missing data and directly implement the updating formula on these complete matrices.

C. Volatility Uncertainty

All of our estimates take as given the estimated volatility and covariance of return series. This approach is motivated by the observation that volatilities are in general much more precisely estimated than means and predictive coefficients. We confirm in our data that uncertainty about volatility only plays a negligible role in our estimation. To do so, we allow Σ_ϵ to be an unknown prior with prior given by an inverse-Wishart distribution, which we choose to be loose. By removing the truncation for the coefficients a_i, we make sure that the variance assumptions do not interact with the truncation, and are able to obtain the Gibbs sampler to draw from the posterior. Indeed, under these assumptions, the priors are conditionally conjugate, so we can alternatively update θ and Σ_ϵ in closed form. To facilitate implementation of the volatility updating, we concentrate on a balanced subsample.

We study our core empirical moment: the cross-sectional slope of elasticities. We compute the elasticity by scaling the predictive coefficient by 0.25 times volatility, which immediately gives rise to a role for uncertainty about volatility. We report the results as a function of the tightness of the prior on predictive coefficients on Figure IA1. The black lines corresponds to our baseline estimate taking variances as given, while the red line is from the procedure we just described. The estimates are only barely smaller for the case of uncertain variance. And, most importantly, the 10-90 range of the posterior is virtually identical to our baseline. In addition, we report in the blue line the elasticity when scaled by expected returns, and assuming no volatility uncertainty. Here we can see that the gain in precision given by shrinking towards a volatility scaling is much larger than any of the small differences due to volatility uncertainty. In summary, uncertainty about volatility only has a negligible impact on the behavior of our estimates, justifying our choice of keeping the analysis simple.

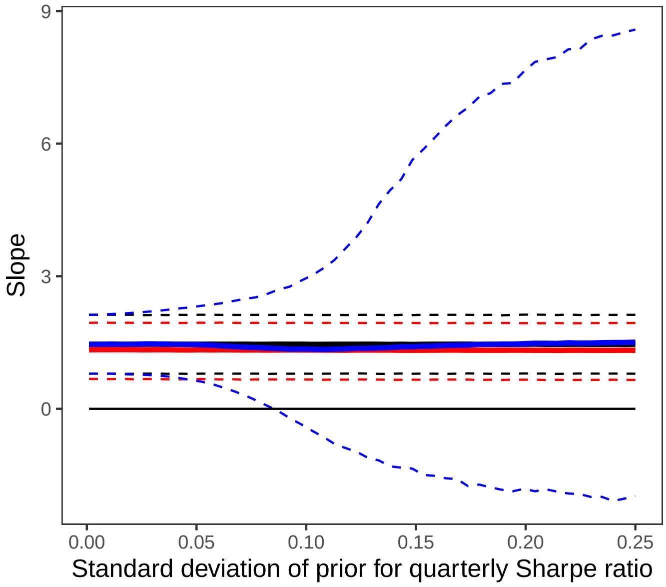


Figure IA1. Role of Variance Estimation.
We report the mean (solid line), 10th, and 90th percentiles (dashed lines) of the cross-sectional slope of elasticities. The black lines assume that variance is known and compute elasticities by $b_i/(0.25\sigma(r_i^\sigma))$. The red lines use the same formula but assume an inverse-Wishart prior for the variance. The blue lines take the variance as given, but measure elasticity by b_i/a_i.

IA.IV. Average Returns in Historical Samples

Golez and Koudijs (2018) study equity returns over four centuries and find an (annualized) market Sharpe ratio of 0.47 for the post war period, and 0.31 for the four hundred year sample as a whole. Gorton and Rouwenhorst (2006) study commodities from 1959-2004 and note in their abstract that "commodity futures historically have offered the same return and Sharpe ratio as U.S. equities". They find a Sharpe ratio of 0.43. Asvanunt and Richardson (2016) state that "the average annual credit excess return [...] over the 1936-2014 period is 137 basis points with a Sharpe ratio of 0.37". They find a Sharpe ratio for US government bonds of 0.31, and they note "the annualized Sharpe ratios across these three primary asset classes (equities, government bonds, and corporate bonds) are quite similar." Giesecke et al. (2011) find a significantly positively credit risk premium of 80 basis points over a 150 year period from 1866-2008. Asness et al. (2012) come to a similar conclusion using data from 1973-2010, finding that stocks, bonds, and credit have similar Sharpe ratios of 0.38, 0.51, and 0.46, respectively. Diep et al. (2017) find the Sharpe ratio on a passive value-weighted MBS index of about 0.3. Lustig et al. (2011) find a Sharpe ratio in FX markets (carry trade) of 0.5 from 1983-2009, stating "currency markets offer Sharpe ratios comparable to... equity markets". Johnson (2017) finds Sharpe ratios of variance sensitive assets ranging from 0.25 to 0.75, with one month straddle returns at 0.5. Borri and Verdelhan (2009) find an average Sharpe ratio for excess returns on sovereign bonds they study of 0.59 from the period 1995-

2011. These findings strongly support the idea of comparable Sharpe ratios across asset classes, with many papers explicitly pointing out that Sharpe ratios are remarkably similar to equities.

IA.V. Credit Risk

The main analysis uses CDS returns as an exposure to credit risk. Table IAI shows regressions using corporate bond returns as an alternative. We use the average excess return of the ICE-BAML investment-grade and high-yield index returns. Notably, the degree of predictability is similar to, though slightly lower than, what we find for CDS in the main text. This makes sense: because CDS and excess corporate bond returns are similar in credit risk exposure, the two returns are highly correlated and hence lead to a similar degree of predictability. However, the two measures are not perfect substitutes, which opens the possibility for some differences. First, they do not focus on the exact same underlying assets. Second, bond positions are exposed to interest rate risk in addition to credit risk. Third, even for individual matched pairs of bond and CDS, pricing deviations sometimes occur, the CDS-bond basis. While intermediaries play a large role in both markets, the CDS market is nearly inaccessible to average investors. This supports the findings in the table that the coefficient, elasticity, and R-squared are all slightly lower when using corporate bond returns vs CDS, but still the degree of predictability of either is much higher than for the stock market.

Table IAI. Intermediary Health and Credit Excess Returns.

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 *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more details.

	(1) CDS	(2) Bonds (Same Sample)	(3) Bonds (Full Sample)
γ_I	0.57***	0.49**	0.33**
	(0.22)	(0.25)	(0.16)
Boots. p-value	0.002	0.038	0.042
Observations	47	47	104
Adjusted R^2	0.316	0.228	0.098
Elasticity			
	2.67	1.42	1.00

IA.VI. Additional Results

Table IAII runs a panel regression with an interaction term for more intermediated asset classes to assess if these asset classes are more predictable by intermediary risk aversion. Table IAIII presents our main table using Newey-West standard errors with 8 lags. Table IAIV shows robustness of our main result when dropping the crisis years of 2007-2009. Table IAV uses only data post 1990.

Figure IA12 shows the plot of coefficients on intermediary risk aversion once controlling for risk (corresponding to Table IAXV in main text). Figure IA2 repeats our analysis with the GZ spread (Gilchrist and Zakrajšek, 2012) (see Table IAX for corresponding Table). Figures IA3 and IA4 split the AEM and HKM measures separately (Tables IAVII and IAVIII give these results in tables). Figure IA5 and Table IAIX uses levels of the AEM and HKM measures instead of annual changes. Table IAXI give results including the habits measure as a proxy for aggregate risk aversion.

Table IAII. Panel Regression: Interaction Effects.

Predictive regressions of future excess returns in each asset class on our proxy for intermediary risk aversion, $\tilde{\gamma}_{I,t}$. We run a panel regression with an interaction term: $r^{\sigma}_{i,t+1} = a_i + b_1 \times \tilde{\gamma}_{I,t} + b_2 \times INT_i \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}$ and report b_2. INT_i represents the degree each asset is intermediated from our ranking. We consider three specifications for INT_i. First, we define INT_i to equal 1 for all asset classes besides stocks and bonds (the two least intermediated according to our rankings). Next we also include options. The last column defines INT_i to equal the rank on a scale from 0 to 1 of all eight of our asset classes. 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 double clustered by time and asset class i.

$INT_i =$	$1_{\neq Stock/Bond}$	$1_{\neq Stock/Bond/Opt}$	Rank $\in$ [0,1]
γ_I	0.06	0.11*	0.08
	(0.05)	(0.06)	(0.06)
$INT_i \times \gamma_I$	0.22***	0.16*	0.29***
	(0.08)	(0.08)	(0.11)
Observations	860	860	860
R^2	0.0511	0.0439	0.0460

Table IAIII. Newey West Standard Errors.

Predictive regressions of future excess returns in each asset class on our proxy for intermediary risk aversion, $\tilde{\gamma}_{I,t}$. We run: $r^{\sigma}_{i,t\to t+1} = a_i + b_i \times \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}$ 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 Newey-West with 8 lags. *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I	0.12	-0.01	0.29***	0.38***	0.18**	0.18**	0.30***	0.57***
	(0.08)	(0.08)	(0.10)	(0.11)	(0.10)	(0.09)	(0.09)	(0.12)
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 IAIV. Excluding the 2007-2009 Financial Crisis.

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. Our sample excludes the crisis years of 2007-2009. 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 *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I	0.11	0.02	0.33***	0.41**	0.26**	0.21*	0.15	0.79***
	(0.10)	(0.08)	(0.12)	(0.21)	(0.12)	(0.12)	(0.14)	(0.31)
Boots. p-value	0.298	0.788	0.003	0.046	0.032	0.072	0.278	0.006
Observations	155	148	91	53	93	104	85	35
Adjusted R^2	0.004	-0.006	0.075	0.081	0.039	0.023	0.004	0.289
Elasticity								
	0.56	0.11	0.56	0.96	0.90	0.49	1.10	2.01

Table IAV. Post-1990 Data.

Note: 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. Our sample uses only data after 1990. 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 *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I	0.23*	-0.00	0.27**	0.38**	0.14	0.13	0.33**	0.57***
	(0.12)	(0.11)	(0.12)	(0.17)	(0.11)	(0.11)	(0.13)	(0.22)
Boots. p-value	0.052	0.986	0.016	0.015	0.214	0.232	0.012	0.005
Observations	92	92	88	65	92	92	92	47
Adjusted R^2	0.040	-0.011	0.060	0.126	0.008	0.005	0.093	0.316
Elasticity								
	1.19	-0.00	0.59	1.03	0.91	0.32	2.76	2.67

Table IAVI. High versus Low γ_I Periods.

Note: Predictive regressions of future excess returns in each asset class on our proxy for intermediary risk aversion, $\tilde{\gamma}_{I,t}$. We run: $r^{\sigma}_{i,t+1} = a_i + b_i \times \tilde{\gamma}_{I,t} + c_i \times \tilde{\gamma}_{I,t} 1_{\tilde{\gamma}_{I,t}>0} + \epsilon_{i,t+1}$ and report b_i and c_i. Excess returns $r^{\sigma}_{i,t+1}$ are normalized by their full sample volatility. $\tilde{\gamma}_{I,t}$ is the standardized AEM intermediary factor. Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the asymptotic standard errors.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I	0.23*	-0.03	0.21	0.66*	0.28*	0.22	0.17	0.91
	(0.14)	(0.16)	(0.19)	(0.34)	(0.16)	(0.20)	(0.22)	(0.63)
$\gamma_I \times 1_{\gamma_I>0}$	-0.19	0.04	0.13	-0.42	-0.17	-0.08	0.24	-0.44
	(0.26)	(0.22)	(0.31)	(0.50)	(0.27)	(0.30)	(0.40)	(0.80)
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.006	-0.013	0.067	0.125	0.015	0.013	0.073	0.312

Table IAVII. AEM Measure.

Note: 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 AEM intermediary factor. Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I^{AEM}	0.13	-0.04	0.24**	0.30***	0.26**	0.16*	0.24**	0.39**
	(0.09)	(0.07)	(0.10)	(0.13)	(0.12)	(0.09)	(0.11)	(0.17)
Boots. p-value	0.137	0.531	0.015	0.010	0.021	0.074	0.031	0.014
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.012	-0.005	0.061	0.114	0.073	0.019	0.062	0.245
Elasticity								
	0.80	-0.18	0.48	0.82	1.27	0.38	1.88	1.80

Table IAVIII. HKM Measure.

Note: 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 HKM intermediary factor. Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I^{HKM}	0.04	0.03	0.12	0.09	-0.06	0.07	0.11	0.12
	(0.09)	(0.07)	(0.12)	(0.14)	(0.14)	(0.09)	(0.12)	(0.16)
Boots. p-value	0.686	0.687	0.338	0.538	0.698	0.475	0.374	0.498
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	-0.005	-0.005	0.006	-0.006	-0.006	-0.004	0.004	-0.003
Elasticity								
	0.23	0.13	0.25	0.25	-0.27	0.16	0.88	0.56

Table IAIX. Levels of AEM and HKM.

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. Our sample excludes the crisis years of 2007-2009. Excess returns $r^{\sigma}_{i,t+1}$ are normalized by their full sample volatility. $\tilde{\gamma}_{I,t}$ is the standardized AEM and HKM intermediary factors in levels. Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I^{level}	0.11	0.01	0.30***	0.69**	0.15	-0.03	0.20	0.65**
	(0.08)	(0.10)	(0.11)	(0.31)	(0.11)	(0.10)	(0.12)	(0.30)
Boots. p-value	0.237	0.949	0.008	0.027	0.195	0.767	0.105	0.024
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.007	-0.006	0.058	0.128	0.006	-0.008	0.016	0.146
Elasticity								
	0.68	0.03	0.60	1.88	0.71	-0.08	1.59	3.03

Table IAX. GZ Spread.

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. Our sample excludes the crisis years of 2007-2009. Excess returns $r^{\sigma}_{i,t+1}$ are normalized by their full sample volatility. $\tilde{\gamma}_{I,t}$ is the Gilchrist Zakrajsek (GZ) spread. Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
GZSpread	-0.03	0.07	0.02	0.18	-0.12	0.02	0.21	0.24
	(0.11)	(0.08)	(0.11)	(0.15)	(0.12)	(0.09)	(0.16)	(0.22)
Boots. p-value	0.808	0.352	0.858	0.299	0.349	0.859	0.217	0.335
Observations	159	153	103	65	105	116	97	47
Adjusted R^2	-0.006	-0.001	-0.009	0.031	0.005	-0.008	0.039	0.065
Elasticity								
	-0.16	0.31	0.05	0.48	-0.57	0.04	1.60	1.13

Table IAXI. Habit.

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 coefficients 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 surplus consumption ratio or habits measure. Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I	0.12	-0.04	0.30***	0.39**	0.22**	0.22**	0.29**	0.72***
	(0.09)	(0.07)	(0.11)	(0.17)	(0.11)	(0.10)	(0.13)	(0.30)
γ_H^{habit}	0.00	0.09	-0.04	-0.03	-0.17	-0.21*	0.03	-0.31
	(0.10)	(0.10)	(0.14)	(0.20)	(0.15)	(0.11)	(0.17)	(0.39)
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.002	-0.005	0.067	0.113	0.035	0.049	0.068	0.351
Elasticity								
γ_I	0.71	-0.16	0.60	1.08	1.07	0.55	2.27	3.34
γ_H^{habit}	0.01	0.39	-0.09	-0.09	-0.84	-0.51	0.24	-1.46

Table IAXII. Price-Dividend Ratio.

Note: 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 coefficients 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 dividend yield of the CRSP value-weighted stock index. Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I	0.12	-0.01	0.29***	0.36**	0.18*	0.18*	0.31**	0.58***
	(0.09)	(0.07)	(0.11)	(0.15)	(0.10)	(0.09)	(0.13)	(0.22)
γ_H^{dp}	0.09	-0.02	0.24*	0.19	0.16	-0.07	0.17	-0.04
	(0.08)	(0.11)	(0.13)	(0.37)	(0.12)	(0.12)	(0.14)	(0.57)
Observations	167	160	103	65	105	116	97	47
Adjusted R^2	0.011	-0.012	0.092	0.116	0.023	0.016	0.079	0.301
Elasticity								
γ_I	0.70	-0.03	0.59	0.97	0.87	0.43	2.44	2.69
γ_H^{dp}	0.54	-0.10	0.50	0.51	0.77	-0.18	1.36	-0.19

Table IAXIII. Decomposing Variation in Expected Return: Statistical Uncertainty.

This table reports the decomposition of Figure 9 at various points in the confidence interval for the predictability slopes across asset classes B_I and B_H. The total amount of expected return variation is held constant, given at the point estimate of the slopes, to focus on uncertainty about the bounds we identify. This total variation in expected returns is reported in the first row. Then, the table reports the fraction of this variation explained by intermediaries and household. Values corresponding to the mean slope — corresponding to Figure 9 — as well as the 5th, 25th, 75th, and 95th percentiles are reported. The percentile distribution of the slopes is computed using the Bayesian estimation procedure described in Section III.B extended to the bivariate case.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
$var(\mathbb{E}_t[r_{t+1}])/var(r_{t+1})$ (%)	3.0	3.4	4.4	5.9	8.0	10.7	14.0	17.8
Percentage due to:								
Intermediaries								
5%	0.0	2.2	7.0	11.7	15.3	17.9	19.7	21.0
25%	0.0	4.7	14.8	24.6	32.2	37.7	41.6	44.4
Mean	0.0	7.0	21.8	36.4	47.6	55.7	61.4	65.6
75%	0.0	9.7	30.3	50.4	66.0	77.2	85.2	90.9
95%	0.0	14.4	44.9	74.8	98.0	114.6	126.4	134.9
Households								
5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25%	5.3	3.5	1.9	0.9	0.4	0.1	0.0	0.0
Mean	41.8	27.3	14.8	7.0	2.9	1.0	0.2	0.0
75%	112.0	73.2	39.7	18.8	7.8	2.6	0.5	0.0
95%	274.6	179.5	97.4	46.1	19.1	6.4	1.2	0.0

Table IAXIV. Predictive Coefficients after Absorbing Conditional Factor Loadings.

Predictive regressions of future excess returns in each asset class on our proxy for intermediary risk aversion, $\tilde{\gamma}_{I,t}$ after absorbing conditional factor loadings. For column 1 to 8, we run: $r_{i,t+1} = a_i + b_{I,i} \times \tilde{\gamma}_{I,t} + \sum_k (\beta_{0,i,k} + \beta_{1,i,k}\tilde{\gamma}_{I,t}) f_{k,t+1} + \epsilon_{i,t+1}$ and report coefficients $b_{I,i}$. Column 9 reports the slope of a regression of these coefficients on a variable growing linearly between 0 and 1 for these asset classes. Excess returns $r_{i,t+1}$ are normalized by their full sample volatility. The baseline does not include any factor. MKT includes the market return. The next row adds the liquidity factor of Pastor and Stambaugh (2003). FF3 is the three-factor model of Fama and French (1993). The next row adds a momentum and short-term reversal factor. The final row also includes the liquidity factor.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit	(9) Slope
Baseline	0.12	-0.01	0.29	0.38	0.18	0.18	0.30	0.57	0.35
MKT	0.00	-0.02	0.19	0.28	0.15	0.12	0.26	0.39	0.32
+ LIQ	0.00	-0.01	0.12	0.29	0.10	0.10	0.24	0.42	0.33
FF3	0.00	-0.02	0.20	0.26	0.17	0.12	0.24	0.29	0.25
+ MOM + ST-REV	0.00	-0.07	0.20	0.26	0.26	0.15	0.29	0.31	0.31
+ MOM + ST-REV + LIQ	0.00	-0.05	0.14	0.27	0.21	0.11	0.27	0.32	0.31

Table IAXV. Intermediary Health and Excess Returns: Controlling for Risk.

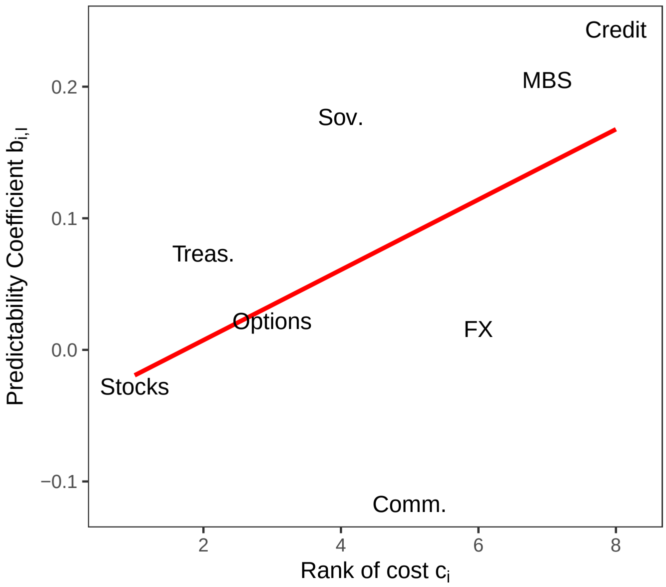
We include changes in risk as controls for our main results. Specifically, we use trailing 3 year (12 quarter) rolling estimates of the volatility of each asset return and trailing 5 year (20 quarter) rolling market betas in each regression (we find we need a slightly longer time period to estimate the betas accurately). Note: Standard errors are computed using the reverse regression approach of Hodrick(1992). *, **, and *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values for intermediary risk aversion are computed using the bootstrap approach described in Section III.A.

	(1) Stocks	(2) Treas.	(3) Options	(4) Sov.	(5) Comm.	(6) FX	(7) MBS	(8) Credit
γ_I	0.07	-0.00	0.33**	0.33*	0.25**	0.19*	0.27**	0.55**
	(0.10)	(0.09)	(0.13)	(0.19)	(0.12)	(0.10)	(0.13)	(0.29)
$\sigma_{i,t}$	0.09	-0.00	-0.02	0.07	-0.17	-0.00	0.16	0.05
	(0.06)	(0.08)	(0.13)	(0.11)	(0.12)	(0.08)	(0.07)	(0.11)
$\beta_{i,t}$		0.24	-0.49	0.01	-0.10	-0.29	-6.10	-3.50
		(1.03)	(0.77)	(0.01)	(0.48)	(0.49)	(6.14)	(5.38)
Boots. p-value	0.499	0.972	0.011	0.060	0.021	0.064	0.025	0.043
Observations	167	151	102	64	104	115	96	46
Adjusted R^2	0.018	-0.020	0.069	0.202	0.181	0.007	0.132	0.322
Elasticity								
	0.40	-0.01	0.66	0.92	1.20	0.47	2.13	2.54

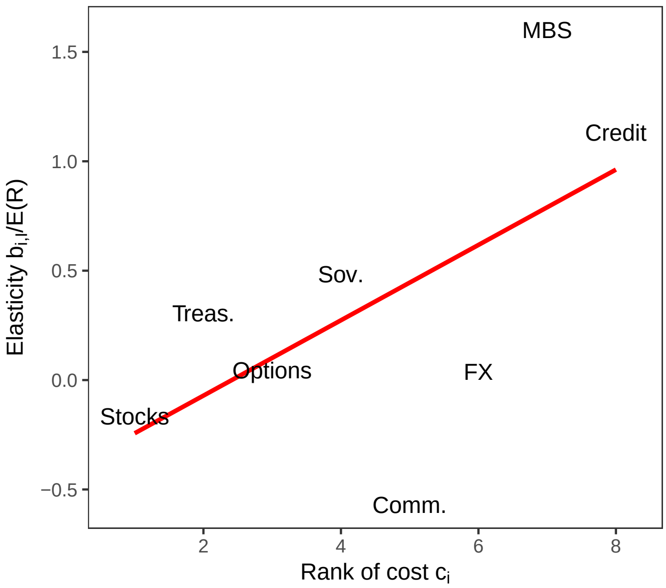
Table IAXVI. Intermediary Health and Hedge Fund Returns.

Predictive regressions of future excess returns 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. 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 *** means statistically different from zero at 10, 5 and 1% level of significance, where the p-values are computed using the bootstrap approach described in Section III.A. The last row, elasticity, computes the elasticity of expected returns as $b_i/E[r^{\sigma}_{i,t+1}]$. See text for more detail.

	(1) Stocks	(2) L-S Equity	(3) Mkt Ntrl	(4) DJCS Index	(5) Evt Drvn	(6) Cvtbl Arb	(7) FI Arb
γ_I	0.12	0.18*	0.13	0.17	0.23*	0.36**	0.29*
	(0.09)	(0.11)	(0.11)	(0.13)	(0.13)	(0.18)	(0.15)
Boots. p-value	0.191	0.099	0.264	0.198	0.073	0.037	0.054
Observations	167	74	74	74	74	74	74
Adjusted R^2	0.008	0.017	0.003	0.014	0.036	0.109	0.068
Elasticity							
	0.71	0.68	1.28	0.52	0.65	1.55	1.96



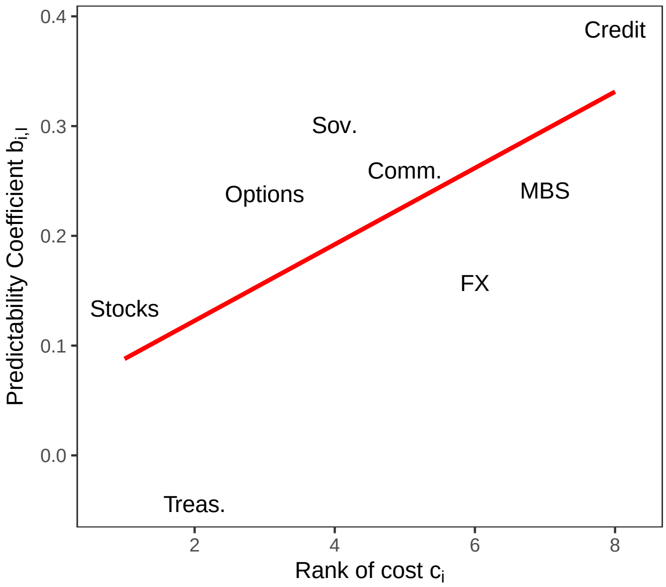
Panel A. Volatility Normalization



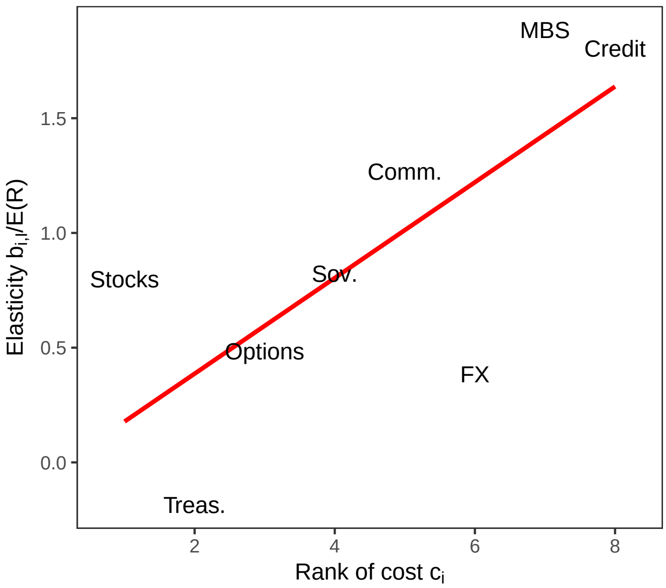
Panel B. Elasticity

Figure IA2. GZ patterns.

Pattern of coefficients.



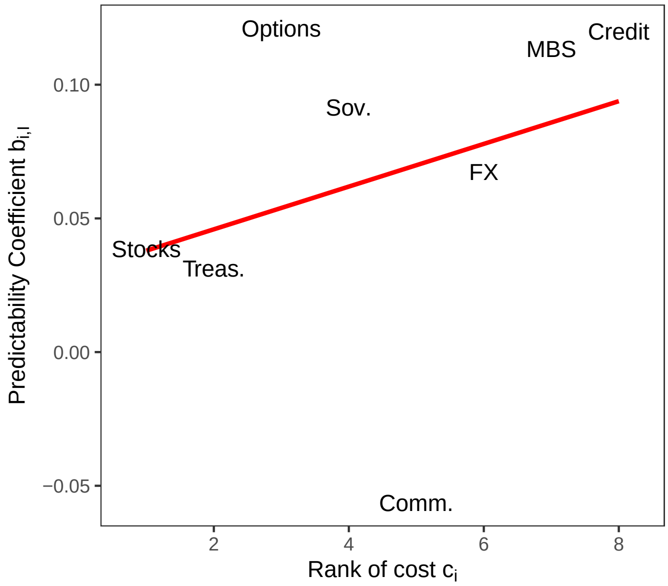
Panel A. Volatility Normalization



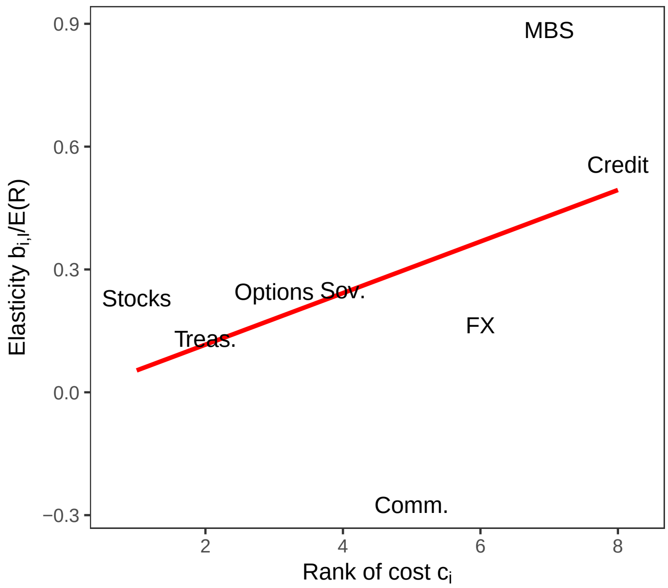
Panel B. Elasticity

Figure IA3. AEM patterns.

Pattern of coefficients.



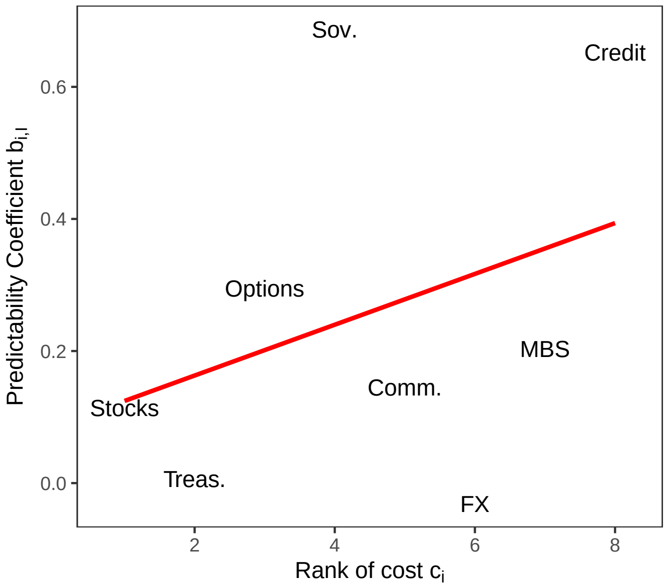
Panel A. Volatility Normalization



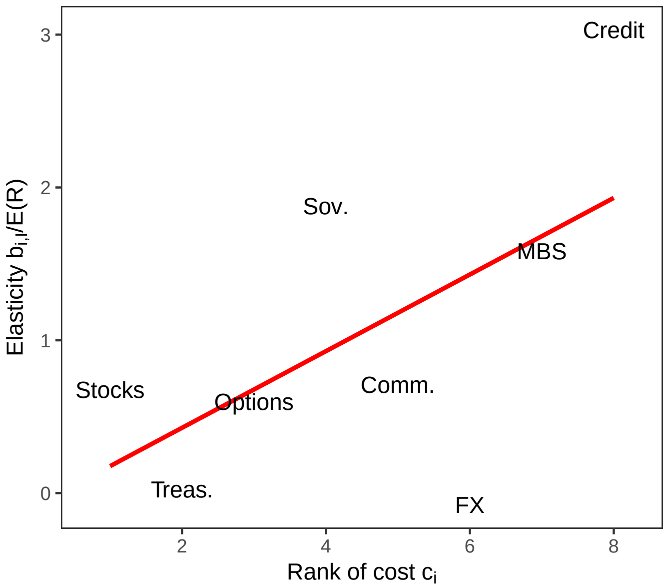
Panel B. Elasticity

Figure IA4. HKM patterns.

Pattern of coefficients.



Panel A. Volatility Normalization



Panel B. Elasticity

Figure IA5. Level patterns.

Pattern of coefficients.

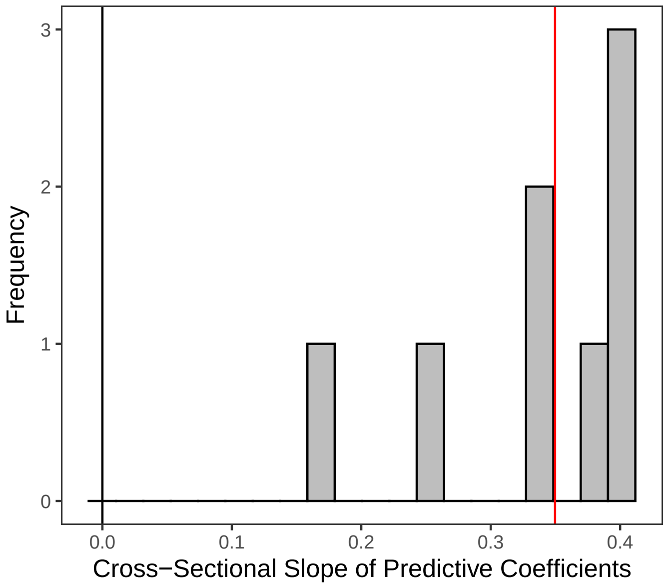
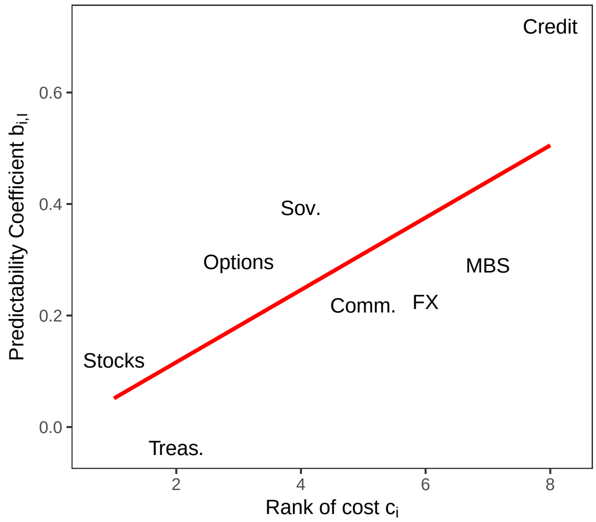
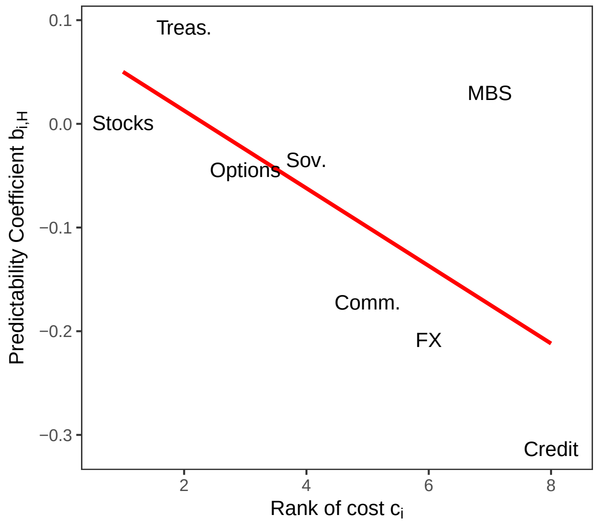


Figure IA6. Predictability across Asset Classes: Eliminating an Asset Class.
This figure plots a histogram of the slope across asset classes in predictive coefficients. Each value corresponds to eliminating one of our 8 asset classes. The red vertical line indicates the slope when using all asset classes.



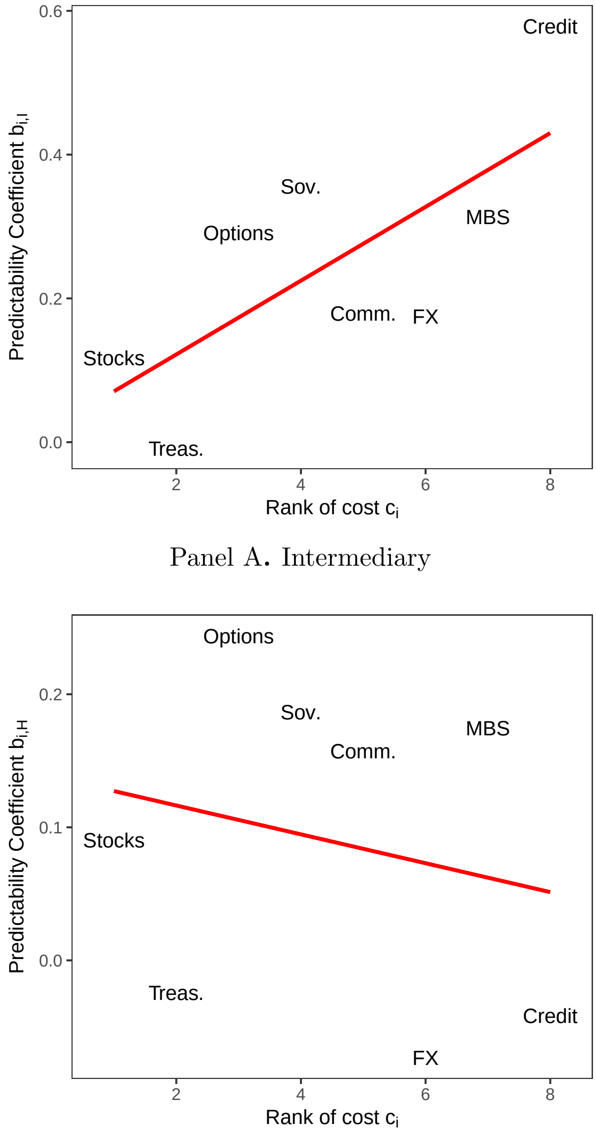
Panel A. Intermediary



Panel B. Habit

Figure IA7. Predictability across Asset Classes: Households versus Intermediaries, using Habit.

We plot coefficients from a predictive regression of excess returns on intermediary effective risk aversion and household risk aversion, proxied by the habit measure. The x-axis is our ranking for how intermediated each asset class is. Panel A shows the pattern of coefficients for intermediaries, and Panel B shows this 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.



Panel A. Intermediary

Panel B. Dividend Yield

Figure IA8. Predictability across Asset Classes: Households versus Intermediaries, using the Price-Dividend Ratio.
We plot coefficients from a predictive regression of excess returns on intermediary effective risk aversion and household risk aversion, proxied by the dividend yield of the CRSP value-weighted portfolio. The x-axis is our ranking for how intermediated each asset class is. Panel A shows the pattern of coefficients for intermediaries, and Panel B shows this 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.

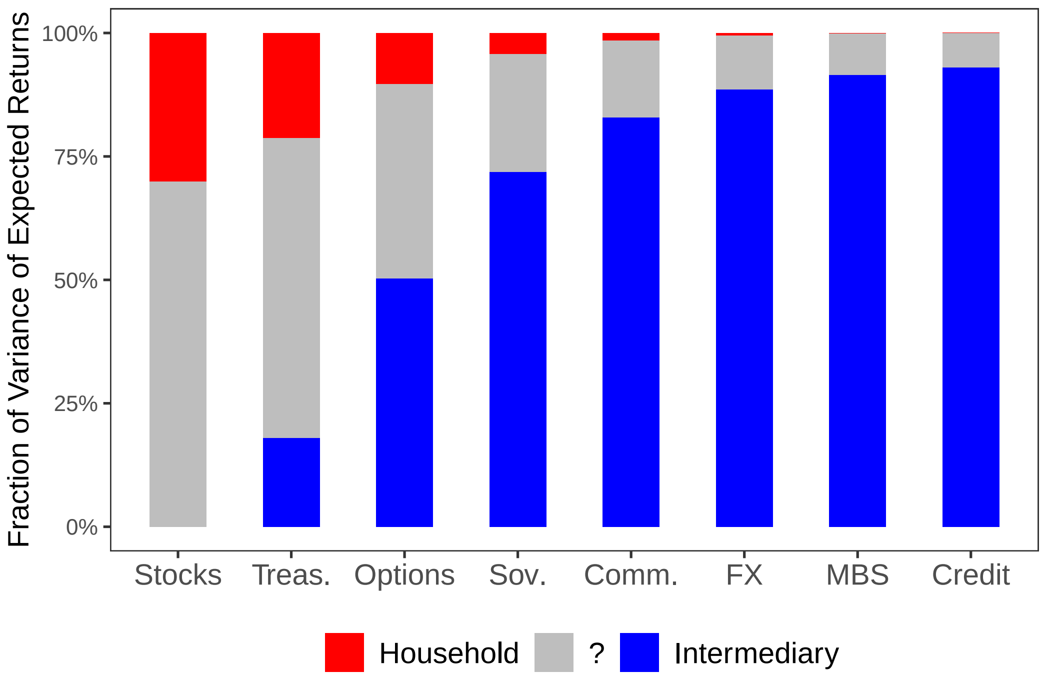
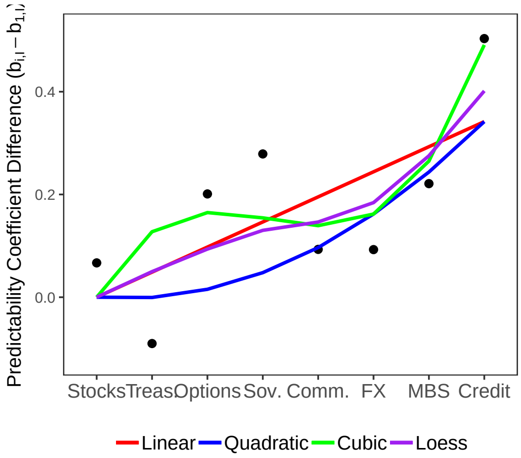
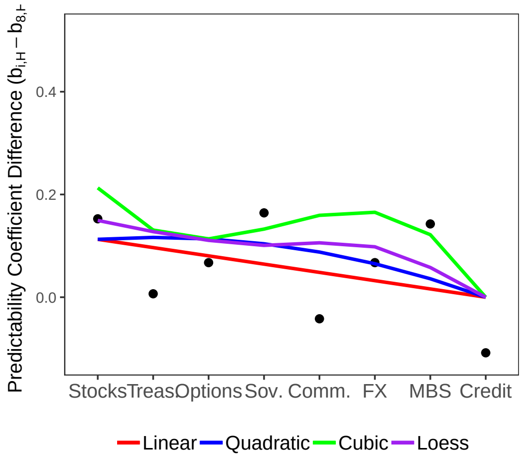


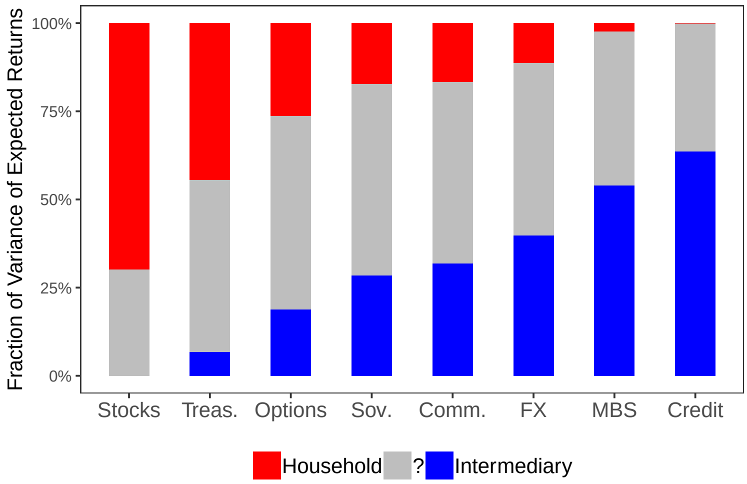
Figure IA9. Decomposition of Risk Premium Variation: Using Elasticities.
This figure plots lower bounds of variation in risk premia coming from households and intermediaries for each asset class using the pattern of predictability across the asset classes. See text for details.



Panel A. Intermediaries



Panel B. Households



Panel C. Decomposition using the Loess Estimate

Figure IA10. Sensitivity to the Linearity Assumption.

Panel A and B reports the lower bound on risk premium standard deviation based on various fit through individual regression results for intermediary and household risk aversion, respectively. Specifically, the figures report the results of a linear, quadratic, and cubic specifications, as well as a local regression (Loess) estimate. Each line plots the fitted $\hat{b}_i - \hat{b}_1$ for intermerdiaries, and $\hat{b}_i - \hat{b}_8$ for households. The black dots are the positions of the point estimates relative to the linear fit. Panel C repeats the decomposition of Figure 9 for the Loess estimate.

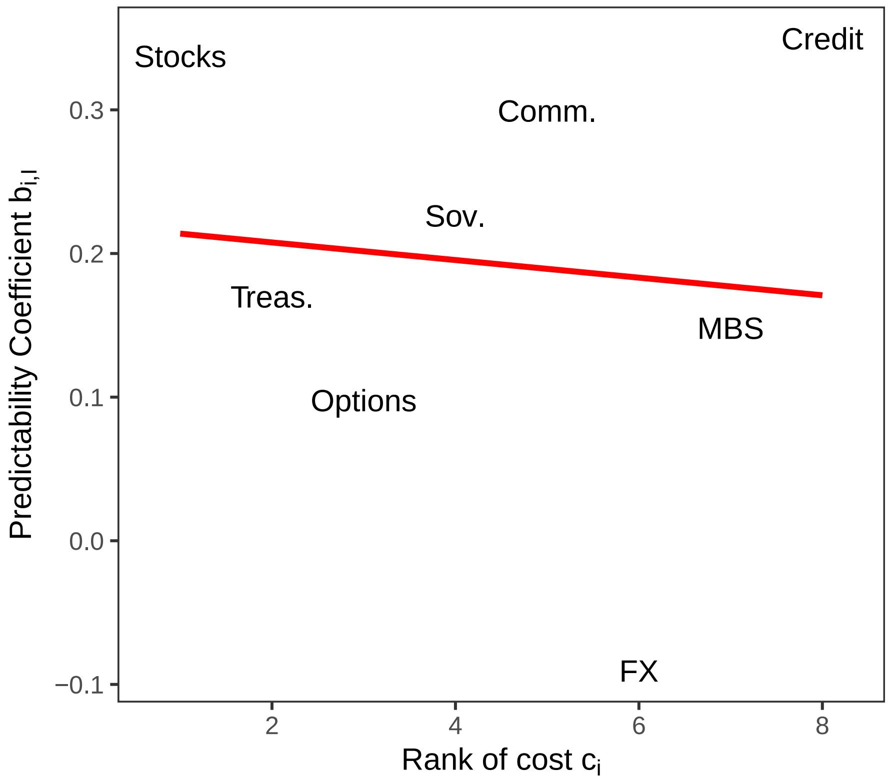
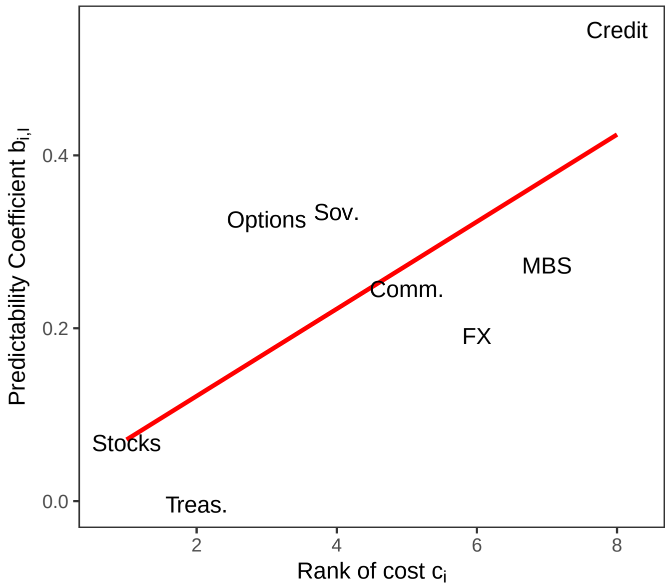
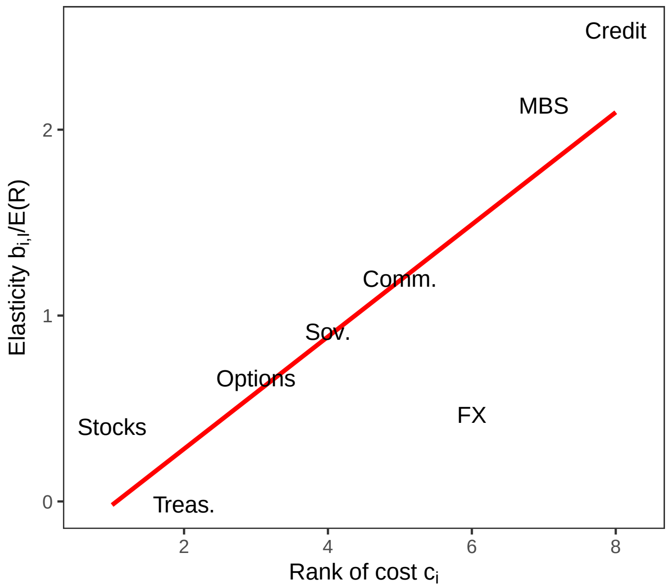


Figure IA11. Predicting Risk using Intermediary Health.
We plot coefficients from predictive regressions of squared excess returns on intermediary effective risk aversion. The coefficients assess whether higher intermediary risk aversion predicts higher risk (variance) in the asset classes. The red line is a linear regression fit through these points. A flat slope indicates that more intermediated asset classes are not relatively riskier when intermediary risk aversion is high. See text for details.

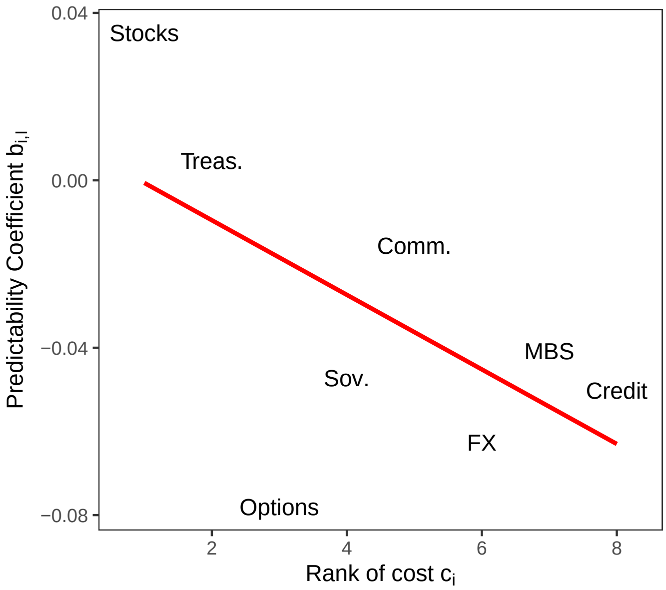


Panel A. Volatility Normalization

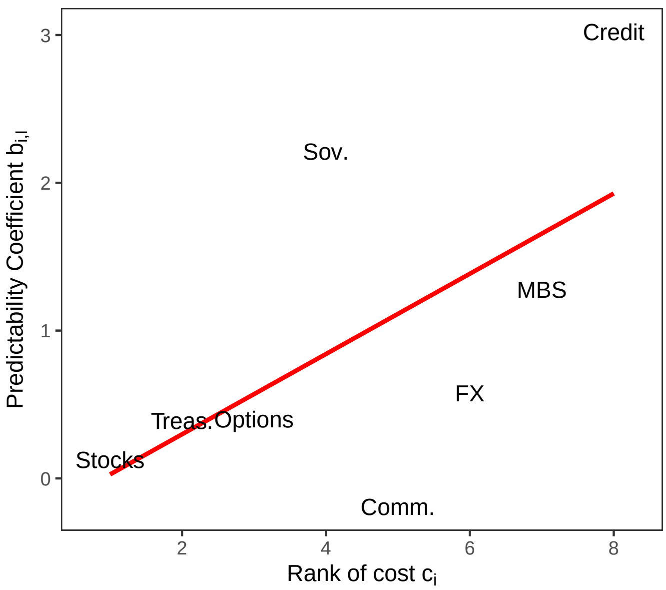


Panel B. Elasticity

Figure IA12. Controlling for risk.
Pattern of coefficients on intermediary risk aversion once controlling for time-varying risk (volatility and beta). See text for details.



Panel A. Large Negative Return



Panel B. Skewness

Figure IA13. Predicting Risk using Intermediary Health: Tail Risk and Skewness.
We plot coefficients from predictive regressions of measured of tail risk on intermediary effective risk aversion. We predict the occurrence of returns below one standard deviation of the mean in panel A and the cubed return in panel B. The red line is a linear regression fit through these points. See text for details.

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