# Leverage Clienteles

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**Abstract**

We present a model in which leveraged and unleveraged investors face uncertainty with regard to margin requirements. We show that under these conditions, investors hedge their risks. Leveraged investors hold portfolios whose returns correlate negatively with the supply of leverage. In contrast, the returns of unleveraged investors correlate positively with leverage supply. We also show that the size of these correlations should be proportional to the expected volatility of the margin requirements. We test these hypotheses using the returns of the most significant type of unleveraged investors, namely mutual funds. We show that, following the financial crisis, mutual funds' returns load positively and significantly on measures of leverage risk across multiple asset classes. We also show that, consistent with the hedging hypothesis, the past loading of mutual funds on the leverage risk factor positively and significantly predicts the future realized volatility of this factor.

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# 1 Introduction

The financial crisis of 2007-2008 has led to increased interest in understanding financial frictions and to a focus on financial intermediaries and their role in determining asset prices. A key finding of this literature, as identified by Adrian et al. (2014) (henceforth 'AEM') and He et al. (2017) (henceforth 'HKM'), is that measures of the capital of financial intermediaries can explain the cross-section of asset prices. Theoretical models, such as Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013), have explained these findings as the result of time variation in margin requirements and subsequent availability of leverage. If investors face an undiversifiable leverage risk, then the returns of assets that correlate with this risk should earn a positive risk premia.

We test and expand these models by analyzing and observing the differences in behavior between various leverage clienteles. We present a model in which leveraged and unleveraged investors face uncertainty regarding margin requirements. We show that under these conditions, investors hedge this risk. Leveraged investors hold portfolios whose returns correlate negatively with the supply of leverage. In contrast, the returns of unleveraged investors correlate positively with leverage supply. We also show that the size of these correlations should be proportional to the expected volatility of the margin requirements. We test these hypotheses using the returns of the most significant type of unleveraged investors, i.e. mutual funds. We show that, across multiple asset classes, following the financial crisis, mutual funds' returns load positively and significantly on measures of leverage risk. Consistent with the hedging hypothesis, we also show that mutual funds past loading on the leverage risk factor positively and significantly predicts the future realized volatility of this factor. We show that they take this exposure through industry tilts toward finance, insurance and real estate firms.

In our model, we present an economy with two types of investors, hedge funds who can leverage, and mutual funds who cannot. Hedge funds are limited in their ability to leverage by a margin requirement. The ratio of this margin requirement is unknown to investors until the requirement goes into effect. We show that a stochastic margin requirement generates opposite risks for the two types of investors. Hedge funds have lower utility when the margin requirement ratio is high, as their ability to leverage is limited and they cannot achieve their desired level of risk. When the margin is low, the hedge funds' increased demand drives current prices higher, lowering the mutual funds' future returns thus lowering their utility.

Investors hedge these risks by deviating from the tangency portfolio, towards a hedging portfolio. Hedge funds choose a hedge portfolio whose returns are higher when the margin requirement is tighter, while mutual funds choose a hedge portfolio whose returns are higher when the margin requirement is less stringent. The size of this hedge is proportional to future volatility in the margin requirement ratio. Because at least one side of this risk market (the mutual funds) is limited in its supply of capital, this hedging behavior does not prevent margin requirement risk from pricing assets.

We test these hypotheses using data from the Morningstar mutual fund database. Morningstar provides comprehensive data on mutual fund returns, holdings, and characteristics encompassing the entire mutual fund industry. We use two common pricing factors as proxies for the margin requirement ratio. Adrian et al. (2014) show that correlation with shocks to aggregate leverage ratios of all broker-dealers has a positive risk price. He et al. (2017) show that shocks to the capital ratio of prime-dealers, in particular, are also related to a positive price of risk and that they do so independently of the aggregated AEM measure. Models such as Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013) show that whether intermediary capital has a positive or negative risk price depends on whether the intermediaries themselves are constrained in their ability to raise equity or raise debt. HKM suggests that both constraints may bind different intermediaries in different settings, explaining how both effects can occur independently.

To evaluate our first hypothesis, we test whether mutual funds' returns have a positive loading on leverage risk factors, controlling for the returns of the market portfolio of the asset class in which they operate. Our empirical results are consistent with the hypothesis presented by our model. We find that, following the financial crisis, the returns of equity mutual funds have a loading on the HKM factor which is both significantly positive and significantly larger than the loading before the crisis. Loading on AEM remains insignificant throughout the entire sample. These results seem to indicate that investors in the equity market are more sensitive to the leverage risk generated by large prime broker-traders than by small and medium broker-traders. As placebo, we test whether mutual funds have a positive loading on other common pricing factors such as value and momentum.

We do not find a significant and positive loading on any of these factors.

To test whether mutual fund hedging is proportional to the expected volatility of margin requirement, we use the realized volatility of leverage risk factor as proxy for the expected volatility. We test whether the loading of mutual funds' returns on the factor, estimated in the past, predict the future volatility of the factor. Consistent with our previous results, we find that variation in equity mutual funds' returns loading on the HKM factor positively and significantly predict future factor volatility. Loading on the AEM factor does not predict future factor volatility, which that the marginal equity market investor is not sensitive to small and medium broker-dealer risk.

To better understand how equity mutual funds' behavior translate into loading on the HKM factor, we analyze the mutual funds' holdings using the Global Industry Classification Standard (GICS). We compare the holdings of mutual funds whose returns had a positive loading on the HKM factor to those whose returns had a negative loading. We find that mutual funds with a positive loading invest more of their AUM in stocks that belong to the finance, insurance, and real estate sectors. We also see a larger holding in traditional industries with high investment and a large amount of physical collateral such as the "Materials" and "Capital Goods" industry groups. Funds whose returns have a negative loading on the HKM factor invest more of their AUM in stock in R&D intensive industries. These include not only industries in the "Information Technology" sector, but also industries such as "Pharmaceuticals", "Biotechnology", "Life Sciences Tools  Services" and "Health Care Technology". We do not find any difference between the two fund types in their holdings on consumer goods industries such as "Food & Staple Retail" and "Household & Personal Product".

The results of our analyses of the fixed income sector of the mutual fund industry are consistent with our hypothesis, yet qualitatively different from our results for the equity mutual fund industry. For the universe of municipal, tax-preferred, bond mutual funds, we observe a positive and significant post-crisis loading on both AEM and HKM. These results are consistent with changes in the municipal bond market over time. Before the crisis, most municipal bonds were insured by AAA-rated mono-line insurance firms. As most of these insurers collapsed during the financial crisis, most municipal bonds are currently uninsured. Therefore, the post-crisis market exhibits a much greater diversity of risks. This heterogeneity is necessary to allow investors to hedge risks. For the universe of high-yield bond mutual funds, we find that the returns display a loading on the AEM factor that is positive and significant. These results imply that the hedging behavior in this market focuses on small and medium dealers as captured by the AEM factor rather than on prime traders as captured by the HKM factor. We also find that this hedging behavior has been ongoing throughout the sample both before and after the crisis.

The rest of the paper is organized as follows. Section II presents a review of the relevant literature. Section III presents a theoretical model of hedging behavior in the presence of uncertain margin constraints. Section IV presents our data and methodology to empirically test the model predictions using the mutual funds' returns. Section V presents our results. Section VI concludes.

## 2 Related Literature

Our work is related to both intermediary asset pricing and the study of mutual fund behavior. Brunnermeier and Pedersen (2009) present a model of intermediary asset pricing in which capital ratios limit the scale of leverage used by leveraged intermediaries.[1] They show that, theoretically, under these conditions, the leverage ratio of levered intermediaries can positively price the cross-section of returns. In contrast, Brunnermeier and Sannikov (2014) present a model in which agency problems limit leveraged intermediaries ability to raise equity to a ratio of their wealth. Under these conditions, they show that capital ratios should positively price assets. He and Krishnamurthy (2013) present a similar model for markets in which households cannot invest directly. In both models, assets are priced by the leveraged intermediaries' risk-bearing capacity. The difference is that, depending on the type of funding constraint faced by the intermediary, leverage ratios (or capital) can directly or inversely proxy this capacity.

These theories have been empirical tested. Adrian et al. (2014) test these models by defining "levered intermediaries" as all broker-dealers who report to the SEC. They find that leverage ratios positively price assets, consistent with Brunnermeier and Pedersen (2009). On the other hand, He et al. (2017) empirically show that, when "leveraged intermediaries" are defined more narrowly as only *prime* dealers, capital positively prices assets. They show that their factor and the AEM factor are not highly correlated, implying that they capture separate effects. To reconcile these results, they present a model with two types of leveraged investors. They show that, given differences in risk aversion between the two types, the *capital ratio* of the more risk-averse intermediaries will have a positive price of risk while the *leverage* of the less risk-averse intermediaries will have a positive price of risk. Hazelkorn et al. (2018) present a specific example of how these mechanisms could operate. They document violations of the no-arbitrage relationship in equity index futures markets and present evidence that ties these violations to the financing frictions of intermediaries.

Our work extends this research by analyzing how non-leveraged investors react to the effect of leverage on asset prices. We show how the leverage clientele affects portfolio choice in the

[1] The intermediary asset pricing literature uses the term "Intermediary" exclusively to denote leveraged, sophisticated intermediaries such as hedge funds and investment banks. To limit confusion, our work will denote these as "leveraged intermediaries" and intermediaries such as mutual funds and pension funds as "un-leveraged intermediaries".

cross-section. By showing that mutual funds have above-market exposure to leverage factors and that this exposure predicts future leverage volatility, we both confirm that the pricing power of these factors is a result of interaction of leverage clientele.

Additionally, our work is related to recent research that documents how markets and market makers have changed following the financial crisis. Adrian et al. (2017), and Adrian et al. (2018) document a stagnation in bank balance sheets following the financial crisis. However, this stagnation has not translated into a significant deterioration in market liquidity. They suggest that this is the result of new actors entering the market for liquidity provision. These results are consistent with our findings that, following the financial crisis, mutual funds may be acting as liquidity providers by overweighing assets that are unappealing to traditional market-makers. Goldberg and Nozawa (2018) show that following the crisis, shocks to dealer capital commitment predict aggregate bond returns.

Finally, our work is related to recent research on how mutual funds choose their loadings on factors beyond the market factor. Barber et al. (2016) show that mutual fund investors evaluate fund performance based only on its CAPM "alpha" i.e. its excess returns after controlling for the market factor. This means that funds with a higher CAPM "alpha" enjoy higher fund flows even if their performance can be explained by their loading on other factors. As this paper analyzes the behavior mutual funds managers, we measure the funds' factor loading relative to the market portfolio. Pástor et al. (2017) show that mutual funds' characteristics affect the funds' portfolio choice. They show that larger funds with lower expense ratios also hold more liquid assets. Lettau et al. (2018) show that, as an industry, equity mutual funds hold stocks with low book-to-market ratio. They also find that mutual funds are market-neutral on other factors such as momentum and profitability. We contribute to this literature by showing that mutual funds load on the leverage risk factors significantly and positively, as opposed to their loading on other commonly observed factors. Boguth and Simutin (2018) show that the average market beta positively predicts the returns of the betting-against-beta portfolio, suggesting that these results represent the time variation in mutual funds' restricted desire to leverage.

Our analysis distinguishes municipal bonds from other similar bonds. This distinction is based on the extensive literature that shows that municipal bonds' unique legal characteristics result in distinct risk and liquidity premia. Pirinsky and Wang (2011) show that, due to its tax-exempt status, the municipal bonds market is highly segmented from other parts of the fixed income market. They show that this market is characterized by significantly different valuations and higher financial intermediation fees. Moldogaziev (2013) documents the collapse of the municipal bond insurance market. Before the financial crisis, most municipal bonds were insured by specialized mono-line insurance firms with a AAA credit rating. During the crisis, all but one of these insurers went into bankruptcy or ceased operation. This led to a divergence between high and low-quality bonds. Marlowe (2013) shows that, before the collapse of the mono-line municipal bond insurers, the municipal bond market was highly liquid with only minimal liquidity risk. Following the collapse, liquidity premiums increased dramatically, with 10-20% of a typical municipal yield spread attributed to liquidity risk. The totality of these results suggest that it is useful to distinguish municipal bonds from corporate, sovereign, or agency debt. Our contribution to this literature is showing how this change was mirrored in their relationship to leverage risk

# 3 Model

## 3.1 Model Setup

The purpose of this model is to understand how leverage risk and uncertainty regarding future margin restrictions affect the portfolio dynamics of investors facing heterogeneous regulatory constraints. Equity investors are a heterogeneous mix of investors: mutual funds, endowments, foundations, sovereign funds and pension funds, which are normally restricted from using leverage, on the one hand and unconstrained investors, such as hedge funds, on the other hand. Leveraged investors face a margin requirement, limiting their ability to leverage to a specific proportion of their capital. Margin requirements vary over time, exposing leveraged investors to increased risk due to uncertainty regarding their future portfolio options. Therefore we would expect hedge funds and mutual funds to construct their portfolios in opposing directions with regard to this risk, allowing the equity market to act as a risk-pooling tool. [2]

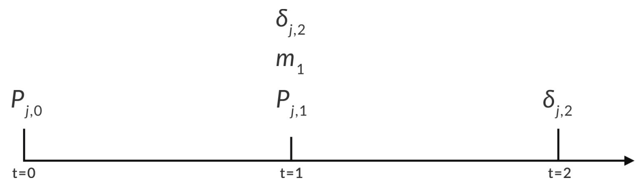
To explore these dynamics, we study an economy with three dates (t=0,1,2), two agent types (mutual funds, "investor 1", and hedge funds, "investor 2"), two risky securities, and a riskless asset.[3] Each security pays two consecutive, uncorrelated, dividends that are unknown at time 0. The first dividend is paid at time 1 and the second dividend is paid at time 2. We label the expected future dividends of security $j$, as $E(\delta_{j,t})$. At time $t$, security $j$ has a price of $P_{j,t}$. Each dividend has a variance of $\sigma_{j,t}$ and a covariance with the dividend of the other asset of $\sigma_{j,-j,t}$. $\boldsymbol{r}$ is the vector of risky assets returns and $\boldsymbol{\Sigma}$ is the variance-covariance matrix of the returns of the risky assets. The riskless rate is $r^f$. We normalize the supply of the assets to 1.

Each investor maximizes their expected return for a given level of variance. There is a large number of investors of each type. Both types have an equal endowment in aggregate at time 0. Each investor $i$ holds $x_{i,j,t}$ of each asset $j$ that forms the vector of holdings $X_{i,t}$. Hedge funds can leverage but, from time 1 onwards, face a margin requirement. This margin requirement is unknown at time 0 but its realization has an expected value of $E(m)$ and a volatility of $\sigma_m^2$. This margin requirement

[2] The contemporaneous and continuous implications of a time variation in margin requirements is explored in papers such as Garleanu and Pedersen (2011). Our model focuses on the forward-looking hedging implication of a time-varying requirement.

[3] It is important to note that our model only refers to active investors. The wealth of passive investors, such as ETFs, should not affect our results.

**Figure 1: Model Timeline**
This figure shows the timeline of our model. At time 0 the assets initial prices ($P_0$) are determined. At time 1 the first two dividend payment ($\delta_{1,1}$ and $\delta_{2,1}$) are revealed as well as the margin ratio requirement $m$. A new set of prices $P_1$ is determined. At time 2 the last two dividend ($\delta_{1,2}$ and $\delta_{2,2}$) are revealed.




implies that total value of hedge funds' positions has to be equal to or smaller than their capital divided by the margin requirement ratio $m$, i.e. $m \sum X_{2,j,1} P_{j,1} \leq W_{2,1}$. Therefore a higher value of $m$ implies more restricted access to leverage. [4] The realization of $m$ at time 1 also has a covariance with the the dividend at period 1 of each security denoted by $\sigma_{j,m,1}$. The dividend of security 1 has a higher correlation with the margin requirement ratio $m$ than security 2 i.e. $\sigma_{1,m,1} > \sigma_{2,m,1}$.

We solve this model by solving for the investors' decision at period 1 and then solving for the investors' decision at time 0 given their expected utility from time 1 and 2. The timeline of the entire model is presented in figure 1.

### 3.2 Investor Portfolio Problem at Time 1

We first analyze investors' decisions at time 1, after the margin and the first dividends of each asset are known.

At period 1, the mutual fund solves:

$$\begin{aligned} &\max_{X_{1,1}} x_{1,1,1} E(\delta_{1,2}) + x_{1,2,1} E(\delta_{2,2}) - (1 + r^f)(x_{1,1,1} P_{1,1} + x_{1,2,1} P_{2,1}) \\ &- \frac{\gamma}{2}(x_{1,1,1}^2 \sigma_{1,1}^2 + x_{1,2,1}^2 \sigma_{2,1}^2 + 2 x_{1,1,1} x_{1,2,1} \sigma_{1,2,1}) \\ &\text{s.t.} \quad \sum x_{1,j,2} P_{j,1} \leq W_{1,1} \end{aligned} \tag{1}$$

[4]For clarity, as it does not effect our predictions, we do not include a margin requirement before time 1.

At period 1, the hedge fund solves:

$$\max_{X_{2,1}} x_{2,1,1}E(\delta_{1,2}) + x_{2,2,1}E(\delta_{2,2}) - (1+r^f)(x_{2,1,1}P_{1,1} + x_{2,2,1}P_{2,1})$$
$$- \frac{\gamma}{2}(x_{2,1,1}^2\sigma_{1,1}^2 + x_{2,2,1}^2\sigma_{2,1}^2 + 2x_{2,1,1}x_{2,2,1}\sigma_{1,2,1}) \tag{2}$$
$$\text{s.t.} \quad m\sum x_{2,j,2}P_{j,1} \leq W_{2,1}$$

Given market clearing:

$$\sum x_{i,1} = 1$$

$$\sum x_{i,2} = 1$$

Therefore the mutual fund's first order conditions are given by:

$$\frac{\partial U_{1,1}}{\partial x_{1,1,1}} = E(\delta_{1,2}) - (1+r^f)P_{1,1} - \gamma(2x_{1,1,1}\sigma_{1,1}^2 + 2x_{1,2,1}\sigma_{1,2,1}) - \phi P_{1,1} = 0 \tag{3}$$

$$\frac{\partial U_{1,1}}{\partial x_{1,2,1}} = E(\delta_{2,2}) - (1+r^f)P_{2,1} - \gamma(2x_{1,2,1}\sigma_{2,1}^2 + 2x_{1,1,1}\sigma_{1,2,1}) - \phi P_{2,1} = 0 \tag{4}$$

The hedge fund's first order conditions are given by:

$$\frac{\partial U_{2,1}}{\partial x_{2,1,1}} = E(\delta_{1,2}) - (1+r^f)P_{1,1} - \gamma(2x_{2,1,1}\sigma_{1,1}^2 + 2x_{2,2,1}\sigma_{1,2,1}) - \tau m P_{1,1} = 0 \tag{5}$$

$$\frac{\partial U_{2,1}}{\partial x_{2,2,1}} = E(\delta_{2,2}) - (1+r^f)P_{2,1} - \gamma(2x_{2,2,1}\sigma_{2,1}^2 + 2x_{2,1,1}\sigma_{1,2,1}) - \tau m P_{2,1} = 0 \tag{6}$$

In equations (3), (4), (5), and (6), $\tau$ and $\phi$ are the Lagrange multiplier for the hedge fund's leverage constraint and the mutual fund's budget constraint.

This equation system is too cumbersome to solved analytically. Therefore, we solve it numerically using the Matlab non-linear system solver "fsolve".[5] We explore the effects of changes in the margin requirement on three variables of interest: the utility of hedge fund at time 1, the utility of the mutual fund at time 1, and the price of the assets.[6]

[5] "fsolve" is based on the trust-region dogleg algorithm.

[6] For clarity, we set the expected dividend such that the margin requirement binds for all values of $m$. Our results hold as long as the margin requirement binds for some possible value of $m$.

Figure 2 plots the utility of the hedge fund and the mutual fund as a function of the margin requirement. The utility of the hedge fund decreases as the margin requirement increases, while the utility of the mutual fund increases. The prices of both assets decrease with the margin requirement.[7] Define $c_i(m)$ as the change in wealth that makes investor $i$ as well off as setting the margin requirement to 0:

$$U_i(W_{i,t} + c_i(m), m) = U_i(W_{i,t}, m = 0) \tag{7}$$

$c_i(m) < 0$ implies the investor $i$ has higher utility when the margin requirement is higher. As the utility of the hedge fund decreases with the margin requirement, we know that the marginal cost to the hedge funds increase as margin requirements increase, $\frac{\partial c_2(m)}{\partial(m)} \geq 0$. Furthermore the marginal cost of margin requirement ratio is higher for the hedge fund fund than the marginal cost for the mutual fund $\frac{\partial c_2(m)}{\partial(m)} \geq \frac{\partial c_1(m)}{\partial(m)}$, which is non-positive, $\frac{\partial c_1(m)}{\partial(m)} \leq 0$. For ease of use, we will refer to $c_i(m)$ as the margin cost of investor $i$.

From the above we can make three observations:

The first observations is that the covariance of the dividend of asset 1 with the margin cost of the hedge fund is higher then the covariance of the dividend of asset 2 with the margin cost of the hedge fund: $\sigma_{1,c_2(m),1} > \sigma_{2,c_2(m),1}$ This is because the margin cost of the hedge fund increases with the margin requirement, which is more correlated with asset 1. Conversely, the covariance of the dividend of asset 1 with the margin cost of the mutual fund is lower then the covariance of the dividend of asset 2 with the margin cost of the mutual fund: $\sigma_{1,c_1(m),1} < \sigma_{2,c_1(m),1}$

The second observation is that, because in our model the only source of differentiation between the assets is the correlation of the dividends with margin requirement, if the covariance of the margin cost of investor $i$ with the dividend of asset $j$ is larger than its covariance with the dividend of asset $-j$, then the correlation of the margin cost of investor $i$ with the *return* of asset $j$ must be larger than its correlation with the return of asset $-j$. Define $\psi_{i,j}$ as the correlation of the margin cost of investor $i$ and the return of asset $j$.

The third observation is that the margin cost is only different from 0 when the margin requirement is binding. If it never binds, the correlation of the cost and the dividend is zero. As

[7]For more on the benefit of mutual funds when margin requirements are tight, see Boguth and Simutin(2018).

we have shown when the margin requirement is binding, $\psi > 0$ , an increase in the volatility of $m$ increases the probability that the margin requirement will bind and thus increases $\psi$. It follows that, an increase in the volatility of $m$ implies an increase in the correlation of the returns with the margin cost of the hedge fund, and a decrease in the margin cost of the mutual fund.

### 3.3 Investor Portfolio Problem at Time 0

As we are interested in the portfolio weights rather than prices, we can focus on the dual problem of finding the minimum variance portfolio for a given target wealth of $\bar{W}$. Therefore, at time 0, investor $i$ is trying to solve the following problem:

$$\min \frac{1}{2}[\sigma_{c_i}^2 + X_{i,0}\psi_i + X_i\mathbf{\Sigma}X_i] + \lambda_i(\bar{W} - W_0[1 + r_f] + X_i(\boldsymbol{r} - r_f\mathbf{1})] - c_i) \tag{8}$$

The portfolio that investor $i$ demands is therefore:

$$X_i = \lambda_s\mathbf{\Sigma^{-1}}(E(\boldsymbol{r}) - r_f\mathbf{1}) - \mathbf{\Sigma^{-1}}\boldsymbol{\psi}_i = A\frac{\mathbf{\Sigma^{-1}}(\boldsymbol{r} - r_f\mathbf{1})}{\mathbf{1}\mathbf{\Sigma^{-1}}(\boldsymbol{r} - r_f\mathbf{1})} + B\frac{\mathbf{\Sigma^{-1}}\boldsymbol{\psi}_i}{\mathbf{1'}\mathbf{\Sigma^{-1}}\boldsymbol{\psi}_i} \tag{9}$$

Therefore, we can see that each investor $i$ holds a mix of the tangency portfolio and a hedge portfolio that is appropriate for his margin requirement risk. We can now aggregate across investors to find the market portfolio:

$$\boldsymbol{M} = \mathbf{\Sigma^{-1}}(E(\boldsymbol{r}) - r_f\mathbf{1})\sum\lambda_i - \mathbf{\Sigma^{-1}}\sum\boldsymbol{\psi}_1 \Rightarrow 2\boldsymbol{M} = 2\mathbf{\Sigma^{-1}}(E(\boldsymbol{r}) - r_f\mathbf{1})\bar{\lambda} - \mathbf{\Sigma^{-1}}\bar{\boldsymbol{\psi}} \tag{10}$$

Where $\bar{\boldsymbol{\psi}}$ and $\bar{\lambda}$ are averaged across both types of investors. We can now find each investor's demand in terms of the market portfolio rather than the unobserved tangency portfolio:

$$X_i = \frac{\lambda_i}{\bar{\lambda}}\boldsymbol{M} - \mathbf{\Sigma^{-1}}(\boldsymbol{\psi}_i - \frac{\lambda_i}{2\bar{\lambda}}\bar{\boldsymbol{\psi}}) \tag{11}$$

As we already established above, $\psi_{2,j}$ has an opposite sign to $corr(r_j, m)$ and $\psi_{1,j}$ has an identical sign to $corr(r_j, m)$ and that both increase with $\sigma_m^2$. Therefore we can state the following testable hypothesis:

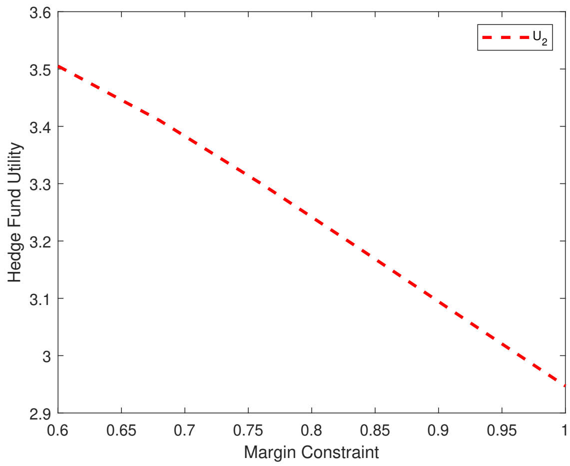
Hypothesis 1: Controlling for exposure to the market portfolio, the total portfolio of the hedge funds should have a negative correlation with the availability of leverage. The total portfolio of mutual funds should have a positive correlation with the availability of leverage.[8]

Hypothesis 2: Controlling for exposure to the market portfolio, the correlation of mutual funds (hedge funds) with the availability of leverage should be higher (decrease) when the expected volatility of the availability of leverage is higher.

[8]It is worth noting that these results hold even if we assume that mutual funds naive investors who are unaware of the risk posed by the availability of leverage. Even if only hedge funds engage in hedging, by market clearing, mutual funds portfolios would still have a positive loading on the availability of leverage.

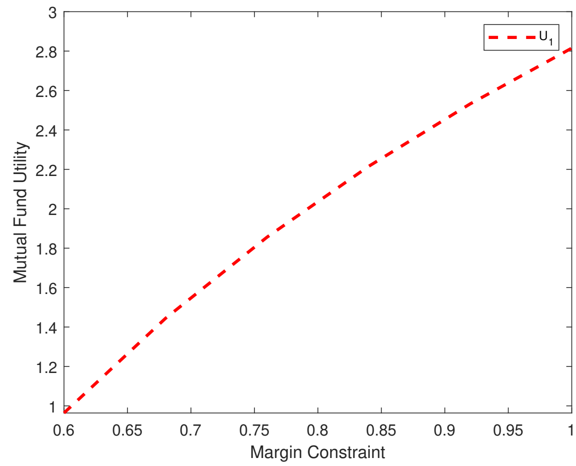
**Figure 2: Model Dynamics - Utility and Margin Requirement**

**(a)** $U_2$ **as a Function of** $m$



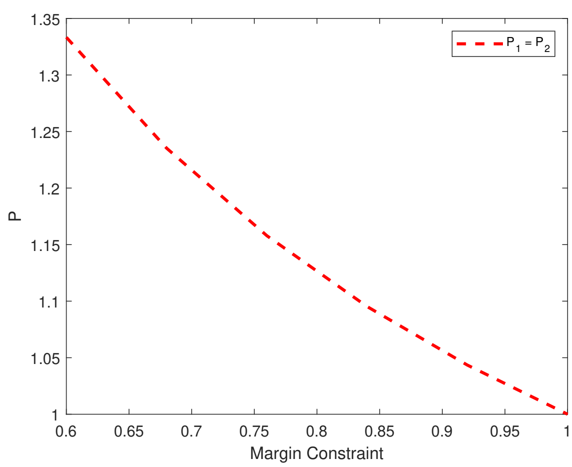

This figure shows the utility of the hedge fund (investor 2) as a function of the margin requirement ratio ($m$). As $m$ increases the hedge fund can leverage less, pushing them farther away from their preferred portfolio, decreasing their utility. The model is calibrated such that the margin requirement constraints bind for every displayed value of $m$.

**(b)** $U_1$ **as a Function of** $m$




This figure shows the utility of mutual fund (investor 1) as a function of the margin requirement ratio ($m$). As $m$ increases prices decrease, increasing the mutual fund utility. Therefore mutual fund utility increases with $m$ for all values of $m$ for which the constraint bind. The model is calibrated such that the margin requirement constraints bind for all displayed values of $m$.

**(c)** $P$ **as a Function of** $m$




This figure shows the prices of the assets ($P_1$ and $P_2$) as a function of the margin requirement ratio ($m$). After the realization of the value of $m$ and the first dividends of the two assets $\delta_{j,1}$, the assets have identical properties going forward. Therefore their prices at this point are identical. As $m$ increases the hedge funds can leverage less, pushing prices down.

# 4 Data and Methodology

## 4.1 Morningstar Data

We acquire fund returns, classification, and AUM from the Morningstar Direct Mutual Fund Database. Morningstar is a leading financial adviser who specializes in researching and rating mutual funds with a comprehensive database going back to the 1980s.[9] Our data cover a period of 17 years, from January 1990 to September 2017. Morningstar classifies funds into “broad category groups”. We focus on funds classified as “Equity”, “Fixed Income” or “Tax Preferred” (i.e. funds that invest only in US municipal bonds). We keep only US-domiciled funds and omit index funds or ETFs.

We further classify fixed-income funds, using Morningstar’s holdings data. Morningstar reports the credit rating profile of the fixed income assets held by a fund. For each quarter, we define a fund as “AAA Fund” if it invested at least 80% or more of its AUM in AAA-rated bonds during that quarter. These percentiles do not include Treasury bonds or notes. We define a fund as a “High Yield Fund” if it invested at least 80% or more of AUM in bonds rated BB or lower during that quarter.[10] To maintain consistency, we adjust for inflation in all AUM data using monthly CPI-U data taken from the St. Louis Fed FRED website.

Morningstar also classifies mutual fund holdings by GICS ("Global Industry Classification Standard") sectors and industries. These classifications are commonly used in the mutual fund industry and therefore can be used to capture the mutual funds’ intended industry exposure. For each fund, we keep quarters for which we can identify the GICS code for at least 80% of AUM. In our final sample, the mean fund-quarter observation has over 95% of its AUM categorized into GICS categories.

We obtain the Market factor from Kenneth French’s website. We obtain HKM, the prime broker

[9] Elton et al. (2001) find the Morningstar database to be more complete and accurate than the CRSP mutual fund database. They note that in 2002 the Morningstar database did not include defunct funds. In recent years this flaw has been corrected, and the database now includes all defunct funds going back to the database’s formation. This addition should minimize the risk of survivorship bias.

[10] Using the same methodology we were also able to classify “Treasury Bond Funds” but the sample of those was too small to allow for statistical analysis. We also used this methodology to omit the few equity funds that hold a significant amount of fixed assets.

capital factor, from Asaf Manela's website. We obtain AEM, the broker leverage factor, from Tyler Muir's website. We use the version of the factor that corrects for Repo market adjustments.[11] We use several different measures as proxies for different types of liquidity. For general equity market liquidity, we use the Pastor and Stambaugh (2003) illiquidity factor from Stambaugh's website. For funding liquidity, we use the Frazzini and Pedersen (2014) "Betting against Beta" factor returns from the AQR website.

To control for market portfolio performance in the various fixed income markets, we use total return indices. For the AAA bond market, we used the "ICE BofAML US Corp AAA" index. For the municipal bond market, we use the "Bloomberg Barclays Municipal Bond Total Return Index". For the high yield market, we use the "ICE BofAML US High Yield Master II Total Return Index". To isolate the credit risk element we deduct from each index return the returns of the "Bloomberg Barclays US Treasuries Total Return unhedged USD index". This deduction allows us to include the credit spread returns and the Treasury index returns separately in each regression. As a robustness check, we examine several alternative indices offered by other providers for each market, but find that these are either identical or almost identical to the main index.

In order to break down the returns of the Treasury yield curve, we use the CRSP Fixed Term Indices with duration ranging from 1 to 20 years. From these we calculated the 20 to 10 year spread, the 10 to 5 year spread and the 5 to 1 year spread.

Tables 1 and 2 summarize fund and factor characteristics. We report the number of funds across equities and fixed income (AAA, high yield, and municipal). The average fund in equities earns 1.9% per annum, has an expense ratio of 1.193, and manages $783.9 million, whereas the average AAA bond fund earns 0.5% per annum, has an expense ratio of 0.710, and manages $485.8 million.

[11] In all of our regressions AEM is only included while controlling for HKM; therefore, we interpret the factor as a proxy for shocks to the risk-bearing capacity of non-prime brokers.

**Table 1: Summary Statistics- Fund Characteristics**

This table reports summary statistics on fund-quarter returns from the Morningstar fund database. The sample includes funds-quarters between 1990 and 2017, excluding ETF or index funds or funds that held less than 80% in any single asset class. We breakdown our sample by asset class (Equity, AAA, High Yield and Municipal). For each asset class we report statistics on fund-quarter returns, sizes and expense ratios. Q Returns are quarterly excess returns. Expense ratio is the percentage of fund assets paid for operating expenses and management fees, including 12b-1 fees, administrative fees, and all other asset-based costs incurred by the fund, except brokerage costs and sales charges . Size is the fund's AUM reported in millions of 1990 dollars.

| | | Mean | StDev | p25 | p50 | p75 | # Fund-Quarters |
|---|---|---|---|---|---|---|---|
| | Q Returns | 0.019 | 0.099 | -0.027 | 0.026 | 0.073 | 244,677 |
| Equity | Size (mill $) | 783.9 | 2976 | 33.135 | 136.9 | 514.5 | 244,677 |
| | Expense Ratio | 1.193 | 0.501 | 0.910 | 1.140 | 1.410 | 210,148 |
| | Q Returns | 0.005 | 0.023 | -0.006 | 0.003 | 0.015 | 16,269 |
| AAA | Size (mill $) | 485.8 | 1707 | 61.004 | 156.6 | 436.4 | 16,269 |
| | Expense Ratio | 0.710 | 0.335 | 0.500 | 0.650 | 0.900 | 14,663 |
| | Q Returns | 0.014 | 0.047 | -0.008 | 0.017 | 0.036 | 6,231 |
| High Yield | Size (mill $) | 608.5 | 1174 | 58.126 | 232.3 | 619 | 6,231 |
| | Expense Ratio | 0.969 | 0.309 | 0.790 | 0.940 | 1.100 | 5,654 |
| | Q Returns | 0.005 | 0.024 | -0.006 | 0.006 | 0.018 | 50,354 |
| Municipal | Size (mill $) | 368.5 | 896.9 | 42.830 | 118.3 | 329.5 | 50,354 |
| | Expense Ratio | 0.727 | 0.297 | 0.550 | 0.730 | 0.860 | 44,000 |

**Table 2: Summary Statistics- Factors & Indices**

This table reports quarterly summary statistics on factor values and index returns. "HKM" is the "Intermediary capital risk factor" from He et al. (2017). The values of the HKM factor are from Asaf Manela's website. "AEM" is the "Broker-Dealer Leverage Factor" from Adrian et al. (2014). The values of the AEM factor are from Tyler Muir's website. Mkt Returns are from Kenneth French's website. "AAA Bond Index" is the "ICE BofAML US Corp AAA" index. "High Yield Index" is the 'ICE BofAML US High Yield Master II Total Return Index". "Municipal Bond Index" is the "Bloomberg Barclays Municipal Bond Total Return Index". To isolate the credit risk element, we deduct from each fixed income index returns the returns of a Treasuries index, namely the "Bloomberg Barclays US Treasuries Total Return unhedged USD index". "Illiq Returns" are the returns of the illiquidity factor from Pastor and Stambaugh (2003). "BaB Returns" are the returns of the Betting-against-Beta factor from Frazzini and Pedersen (2014).

| | Mean | StDev | p25 | p50 | p75 |
|---|---|---|---|---|---|
| HKM Factor | 0.016 | 0.125 | -0.042 | 0.028 | 0.085 |
| AEM Factor | -0.001 | 0.069 | -0.032 | 0.005 | 0.045 |
| Mkt Return | 0.020 | 0.081 | -0.018 | 0.030 | 0.066 |
| Treasuries Index | 0.014 | 0.025 | -0.004 | 0.012 | 0.033 |
| AAA Bond Index | 0.001 | 0.013 | -0.002 | 0.003 | 0.007 |
| High Yield Index | 0.008 | 0.058 | -0.010 | 0.013 | 0.037 |
| Municipal Bond Index | 0 | 0.019 | -0.009 | 0.001 | 0.010 |
| Illiq Returns | 0.012 | 0.072 | -0.026 | 0.010 | 0.057 |
| BaB Returns | 0.023 | 0.075 | -0.009 | 0.024 | 0.065 |

## 4.2 Time Series Regressions

Our model implies that, under reasonable assumptions, the returns of unleveraged investors such as mutual funds will have a positive loading on leverage cost risk. We proxy for this factor using the factors suggested by He et al. (2017) and Adrian et al. (2014) (henceforth called "Intermediary Pricing Factors" or "IPF"). Therefore, if $\beta_{IPF}$ is the loading of mutual funds' returns on the intermediary pricing factor, our null hypothesis is:

**Hypothesis 1**: $\beta_{IPF} = 0$, which we reject if $H_1$: $\beta_{IPF} > 0$

In each regression specification, we include both the HKM factor, which captures prime broker-dealers' risk-bearing capacity, and the AEM factor, which captures non-prime broker-dealer risk-bearing capacity.

Our model suggests that the loading on the factors should be relative to the funds' investment opportunities. As neither IPF is a factor of returns, there is no reason to assume that a fund's "natural" loading would be zero. Fortunately, in the case of mutual funds, the possible investment opportunities are well defined. Each mutual fund in our sample only owns securities in its predesignated asset class. Therefore, we measure its performance against an index of that asset class. As mentioned in Section 4.1, we focus on mutual funds belonging to the following major industry classifications: (a) equity funds, (b) AAA bonds funds, (c) high-yield bonds funds and (d) municipal bond funds.[12] For each asset class, we control for the return of a value-weighted index of that class. Following HKM, we also control for the equity market factor in all regressions. These controls allow us to rule out the claim that mutual funds only load positively on IPFs because their underlying asset class loads positively on the IPFs.

A possible confounding variable for our test is the correlation with the returns of a portfolio with exposure to market illiquidity. If assets that correlate with IPFs are also illiquid, it could be that a positive loading on the IPFs is only capturing a willingness by mutual funds to maintain an illiquid portfolio. To rule this out, we include an additional set of controls to capture loadings on both market and funding liquidity. *Illiq* is Pastor and Stambaugh (2003)'s returns for market illiquidity. *BAB* is the Frazzini and Pedersen (2014)'s Betting-Against-Beta return. *TEDSpread* is

[12] Due to their unique tax treatment, municipal bonds are generally held by specialized funds.

the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill.

For each quarter we calculate the return of the mutual fund asset class sector (Equity, AAA, High Yield and Municipal) as the size-weighted mean return of all funds in that sector in that quarter.

Therefore our initial rolling regression specification is:

$$r_t = \alpha + \beta_1 AEM_t + \beta_2 HKM_t + \beta X_t + \beta_4 r_{mkt} + \beta_5 r_{index} + \sigma_t \tag{12}$$

where $r_t$ is the return of the fund sector at quarter $t$. $AEM_t$ and $HKM_t$ are the values of the HKM and AEM factors at quarter $t$, $r_{mkt}$ is the return of the equity market portfolio, $r_{index}$ is the return of the funds' asset class market portfolio. For fixed-income asset classes, we separately control for the Treasury index returns and the asset class risk spread. We use Newey-West standard errors with automated lag selection (see, e.g. Newey and West (1994)).

The 2007 financial crisis has greatly increased the salience of leverage cost risk. This suggests that the willingness of hedge funds to hedge this risk might have increased following the crisis. To test this, in our second regression specification, for each of the IPFs, we add an interaction with a dummy variable $PCrisis$ that equal 1 if the quarter was after the third quarter of 2008.

$$\begin{aligned} r_t =& \alpha + \beta_1 AEM_t + \beta_2 HKM_t + \beta_3 r_m + \beta_4 r_{index} + \beta_5 PCrisis \times AEM_t \\ &+ \beta_6 PCrisis \times HKM_t + \beta_7 PCrisis \times r_m + \beta_8 PCrisis \times r_{index} + \epsilon_t \end{aligned} \tag{13}$$

Finally, we test whether the post-crisis loading itself is positive by running the original time series regression using the post-crisis returns.

### 4.3 Panel Regressions and Volatility Predictability Tests

An implication of our model is that the loading on the IPFs reflects market participants' desire to hedge future risk. Therefore the model predicts that IPF loading should correlate with expected IPF volatility. We can proxy expected for IPF volatility with realized IPF volatility. Therefore, if $\beta_{IPF,t}$ is the loading of the mutual fund sector on the leverage factor at time $t$ and $Var(IPF)_{t+1,T}$ is the future volatility of the IPF, and $\beta_{\beta,Cov}$ is the regression coefficient of $\beta_{IPF,t}$ on $Var(IPF)_{t+1,T}$, our null hypothesis is:

**Hypothesis 2**: $H_0$: $\beta_{\beta,Cov} = 0$ which we reject if $H_1$: $\beta_{\beta,Cov} > 0$

Testing this hypothesis requires a time series of the loading of the mutual fund industry on each IPF. As the IPFs are quarterly data-points, using rolling time series regressions may result in "stale" betas. Therefore we use a rolling panel regression. We replicate our original regression specification for each fund for each quarter using a 5 year window. Following the Pástor et al. (2017) finding that a fund's choice of factor loading might be affected by its AUM and its expense ratio, we control for both fund characteristics in each regression.

Therefore our panel regression specification is:

$$r_{i,t} = \alpha + \beta_1 AEM_t + \beta_2 HKM_t + \beta X_{i,t} + \beta_4 r_{mkt} + \beta_5 r_{index,t} + a_i + \epsilon_t \qquad (14)$$

where $r_{i,t}$ is the return of fund $i$ in quarter $t$, $a_i$ is a fixed effect for fund $i$, and $X$ is a vector of fund-specific controls, namely, fund AUM, and expense ratio. Each fund is weighted by size. We cluster standard errors by fund and date.

We define the time series of $\beta_{IPF,t}$ as $FHedge$ as it should be a measure of the hedge of mutual funds on leverage risk. If this is true, $FHedge_t$ should positively predict $Vol(IPF)_{t+1,T+1}$. Testing this directly faces the difficulty that $Vol(IPF)_{t-T,t}$ is negatively correlated with $\beta_{IPF,t}$ and that volatility can be highly autocorrelated. To overcome this, we use the first difference of $Vol(IPF)$ to reduce autocorrelation and look ahead bias. We then run an augmented Dickey–Fuller test on the resulting $\Delta Vol$ to rule out a unit-root process. In addition, we control for $Vol_{t-T,t}$ in case $Vol$ is correlated with $\Delta Vol$. Finally, we control for the mutual fund industry loading on market risk $\beta_{mrk,t}$ and illiquidity $\beta_{Illiq,t}$.

## 4.4 Industry Holding Analysis

To acquire an understanding of mutual funds' behavior with regards to the IPFs, we analyze mutual funds holdings using the Global Industry Classification Standard (GICS). GICS is a industry taxonomy developed by S&P and MSCI in 1999. This taxonomy is widely used in the mutual fund industry to classify stocks.

In order to explain mutual funds' IPF exposure in terms of its holding we require a per-fund time series estimate of its loading on each IPF. For each fund we run a rolling regression of its returns on IPFs, market returns, and illiquidity. Then, for each quarter, for each IPF, we split funds by into two groups: funds with a negative loading on the IPF and funds with a positive loading on the IPF. We then calculate the AUM weighted percentage held in each sector, industry group and industry[13] for each mutual fund type (positive and negative IPF beta). We omit the "Mortgage REITs" and "Entertainment" industries as these were only defined as distinct industries towards the end of our sample. We then calculate the difference between the two types for each sector, industry group, and industry and test whether this difference is significant using Newey-West SE.

[13]"Sectors" are the GICS' two digits categories, "Industry Groups" are the four digits categories, and "Industries" are the six digits categories.

# 5 Results

## 5.1 Factor Loading Estimation

Our first hypothesis is that mutual funds should have a positive dynamic loading on leverage risk factors. We explore this prediction using a series of time-series regressions of the returns of the mutual fund industry on the leverage risk factors, as we present in Subsection 4.2, Equation 12 and Equation 13. As the motivation for this behavior is hedging, we would expect this loading to increase following the financial crisis, as the risk becomes far more salient. To test this, we add the interaction variables of the intermediary factors and the post-crisis dummy. To test whether the post crisis loading is positive we re-run our original regression using only the post-crisis sample.

Table 3 reports the results of our analysis. While the column (1) shows that we do not find a significant loading in the period leading up to the crisis, columns (2), (3), and (4) show that the interaction of the post-crisis factor and the loading on HKM after the crisis is positive and significant, implying that the loading following the crisis was greater than the loading before the crisis. Columns (5) and (6) show that, following the crisis, the loading on the HKM is positive and significant. The loading on AEM remains insignificant during the entire sample. These results indicate that investors in the equity market are more sensitive to the leverage risk generated by large prime broker-traders than by small and medium broker-traders. This seems to imply that the large prime dealers are the main providers of leverage in the equity market. Controlling for funding liquidity measures slightly increases the size and significance of our results. As a placebo, we repeat our regression specifications for each of the Fama-French factors and the momentum factor. We do not find a significantly positive loading on any of the factors either before or after the crisis. These results are consistent with the notion that sophisticated leveraged investors do not allow themselves to gain negative exposure to factors that have a positive price of risk.[14]

[14]Our results are mostly consistent with the results of Lettau et al. (2018) with the exception that they also found a negative loading on value factor. This difference might be the result of our use of mutual fund returns compared with their use of mutual fund end of quarter holdings.

**Table 3: Equity Funds Time Series Regressions**

The dependent variable is $REquity_t$, the excess return of the equity mutual fund industry at time $t$. $PCrisis$ is a dummy variable for when the quarter is later then Q3, 2008. All other controls are defined in Table 1. In each regression specifications, we also include, but do not report, the market return, $PCrisis$ and interaction of all controls (including market) with $PCrisis$. Columns (2), (3), and (4) test the interaction of $PCrisis$ and the intermediary asset pricing factors. Columns (5) and (6) include only the post-crisis part of the sample. Columns (3), (4), and (6) include the funding liquidity controls. $t$-statistics based on Newey-West standard errors with automatic lag selection are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Q4-1989<t<Q4-2017 | $PC$ | $TEDSPREAD$ | $BAB$ | t>Q3-2008 | t>Q3-2008 |
| $HKM_t$ | 0.007 | -0.027 | -0.035 | -0.036 | 0.050** | 0.064*** |
| | (0.35) | (-1.10) | (-1.53) | (-1.45) | (2.31) | (2.77) |
| $AEM_t$ | 0.004 | 0.009 | -0.013 | -0.013 | -0.013 | 0.021 |
| | (0.16) | (0.28) | (-0.44) | (-0.42) | (-0.42) | (0.51) |
| $IlliquidityR_t$ | 0.097*** | 0.088*** | 0.078*** | 0.078*** | 0.027 | 0.041 |
| | (3.81) | (3.48) | (3.23) | (3.25) | (0.75) | (1.15) |
| $HKM \times PCrisis$ | | 0.077** | 0.086** | 0.100*** | | |
| | | (2.15) | (2.55) | (2.69) | | |
| $AEM \times PCrisis$ | | -0.021 | 0.027 | 0.035 | | |
| | | (-0.41) | (0.42) | (0.52) | | |
| $TedSpread$ | | | -0.022*** | -0.021*** | | 0.003 |
| | | | (-3.96) | (-3.38) | | (0.37) |
| $BABR_t$ | | | | 0.000 | | -0.077 |
| | | | | (0.01) | | (-1.36) |
| Constant | -0.003 | -0.003 | 0.010*** | 0.010** | -0.004* | -0.002 |
| | (-1.54) | (-1.59) | (2.76) | (2.26) | (-1.82) | (-0.54) |
| N | 111 | 111 | 111 | 111 | 36 | 36 |
| $R^2$ | 0.93 | 0.93 | 0.94 | 0.94 | 0.97 | 0.97 |
| Market Index | YES | YES | YES | YES | YES | YES |
| Post-Crisis Controls | YES | YES | YES | YES | YES | YES |

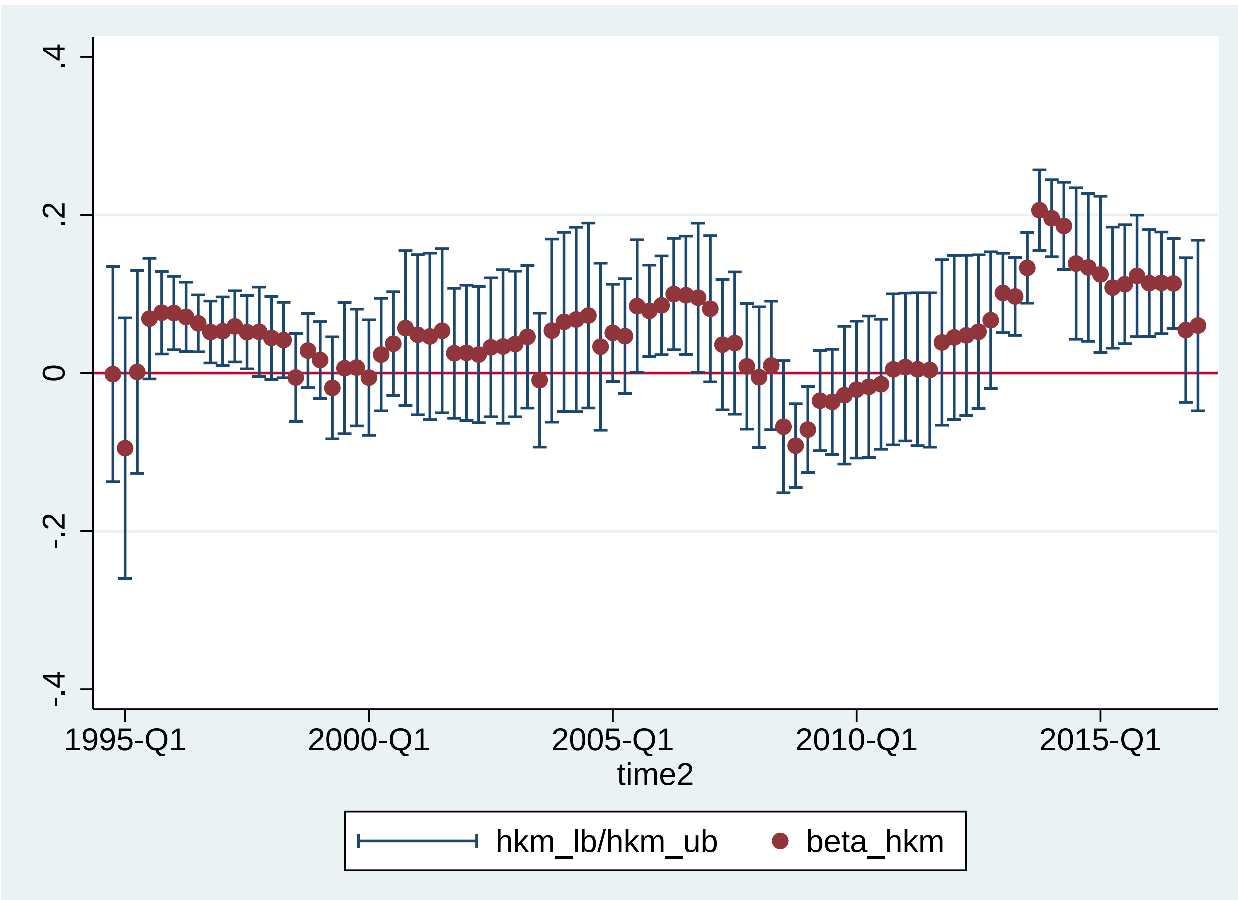
t-statistics in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 5.2 Volatility Estimation

If the mutual funds' loading on the leverage risk factors reflects a hedging behavior, we would expect the funds' loading to be correlated with expected factor volatility. Testing this requires us to produce a time series of the mutual fund industry's loadings on the factors. To do so, we run a panel regression of mutual fund returns on the leverage risk factors, as we present in Subsection 4.3, Equation 14.

**Figure 3: HKM Factor Loading Rolling Regressions**




This figure shows the loading of the equity mutual fund industry on the HKM factor. Each point estimate is the HKM beta from a panel regression of equity mutual funds returns on the HKM, AEM, Pastor-Stambaugh and market factor. Each regressions uses a 5 years rolling window. We also controlled for the TED-Spread, mutual funds size, expense ratio and fund fixed effects. Results are weighted by size. SE are clustered by fund and time.

Figure 3 shows that the results of the panel regressions are consistent with the results of the time series regression. The loading on the HKM factor increases and becomes significantly positive following the crisis. We proxy expected volatility using realized future volatility. In order to distinguish the effect of small and medium dealers from the effect of prime dealers, we regress HKM on AEM and AEM on HKM and estimate the volatility of the residuals. We estimate volatility over periods of 3, 4.5, and 6 years.

Regressing a factor's volatility on its beta presents a challenge as volatility can be autocorrelated thus, by construction, beta is negatively correlated with contemporaneous volatility. We overcome this challenge using a number of approaches. First, to deal with auto-correlation and look ahead bias we transform the volatility series into a series of first differences, $\Delta VolHKM$ and $\Delta VolAEM$. We then perform an augmented Dickey-Fuller test to confirm that these series are not a unit-root process.

Table 4 shows the results of these regressions for the volatility estimation windows. Consistent with our hypothesis, the mutual funds' loading on the HKM factor positively and significantly predicts future factor volatility. The loading on the AEM factor does not predict future volatility, which again indicates that equity market investors are not sensitive to small and medium dealer risk.

**Table 4: Volatility Predictability Regressions**.

The dependent variable is $\Delta VolResidualHKM_{t,t+T}$, the first difference of the volatility of the residuals of the HKM factor, controlling for the AEM factor, estimated over periods of 3 years, 4.5 years and 6 years. $BetaHKM_{t-1}$ is the equity mutual fund industry's loading at time $t-1$, i.e with an estimation window that ends one period before the beginning of the estimation window of $\Delta VolResidualHKM_{t,t+T}$. In columns (2), (3), (4), and (5) we include controls for the equity mutual fund industry's loading on the market and the illiquidity factor. In columns (3), (4), and (5) we include controls for $VolResidualHKM_{t-1,t-T-1}$, the volatility of the residuals of the HKM factor, estimated with a a one period gap, using the same size estimation window as $\Delta VolResidualHKM_{t,t+T}$. $t$-statistics based on Newey-West standard errors with automatic lag selection are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | $3YF.Vol$ | $3YF.Vol$ | $3YF.Vol$ | $4.5YF.Vol$ | $6YF.Vol$ |
| $HKMBeta_{t-13}$ | 0.039*** | 0.042** | 0.046** | | |
| | (3.93) | (2.48) | (2.57) | | |
| $HKMBeta_{t-19}$ | | | | 0.044*** | |
| | | | | (4.21) | |
| $HKMBeta_{t-25}$ | | | | | 0.021** |
| | | | | | (2.29) |
| Constant | -0.002*** | -0.002 | -0.002 | -0.007* | -0.001 |
| | (-2.61) | (-0.31) | (-0.31) | (-1.72) | (-0.18) |
| N | 79 | 79 | 78 | 72 | 66 |
| $R^2$ | 0.18 | 0.18 | 0.19 | 0.32 | 0.26 |
| Vol Controls | NO | NO | YES | YES | YES |
| Market Beta Controls | NO | YES | YES | YES | YES |
| Illiqudity Beta Controls | NO | YES | YES | YES | YES |

t-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

### 5.3 Robustness Checks

Considering the long periods we use to estimate factor volatility, we wish to examine how far ahead the market is able to predict volatility. We do so by progressively extending the gap between the volatility estimation window and the beta estimation window. We find that, for all estimation windows, beta is no longer significant if the gap is extended beyond 1-2 years. This implies that, while the market has some ability to predict future volatility, this ability does not extend very far into the future.

In addition, we also perform the following robustness checks and observe that, in all cases, the results remain positive and significant. First, we exclude the years 2008 and 2009 to lessen the importance of the financial crisis on our results. Second, instead of using $\beta_{HKM}$ we estimated the partial cross-sectional correlations of mutual fund returns on the HKM factor and used those instead. Third, instead of $\beta_{HKM}$, we use the first differences of the betas, $\Delta\beta_{HKM}$.

### 5.4 Industry Holding Analysis

Table 5 presents the differences in industry holdings between equity mutual funds with a positive $\beta_{HKM}$ and funds with a negative $\beta_{HKM}$.[15] As expected from the definition of HKM, we see that positive $\beta_{HKM}$ funds hold a higher percentage of their AUM in banking stocks. We also see larger holdings in every industry in the finance sector, insurance sector, and the real estate sector. This is known among mutual fund investors as a “FIRE”. We also see significantly larger holdings in traditional high investment industries such as the “Materials” and “Capital Goods” industry groups.

Positive $\beta_{HKM}$ funds hold a lower percentage of their AUM in stocks in almost every industry in the “Information Technology” sector. We also see lower holdings in other R&D intensive industries outside of this sector such as “Pharmaceuticals”, “Biotechnology”, “Life Sciences Tools & Services” and “Health Care Technology”.

These results show that, regardless of whether mutual fund managers are aware of the specific risk premia of the leverage factor, their positive loading on this factor is the result of a coherent investment strategy in specific industries.

[15]For the sake of brevity, we include only industry groups that are significantly different between the types.

## Table 5: Industry Holding Spread.

This table presents the difference in holdings between equity mutual funds with a positive $\beta_{HKM}$ and funds with a negative $\beta_{HKM}$. "Mean Difference" is the mean difference in % of AUM between the quarterly average of positive $\beta_{HKM}$ and negative $\beta_{HKM}$ funds. "Industry Groups" are 4 digit GICS classifications. "Industries" are 6 digit GICS classifications. $t$-statistics based on Newey-West standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | Difference | | Difference | | Difference |
|---|---|---|---|---|---|
| **Materials** | 0.853** | Airlines | 0.032 | **DiverFinancial** | 1.979*** |
| | (2.23) | | (0.24) | | (4.47) |
| Chemicals | -0.101 | Marine | 0.058*** | DiverFinancialServ | 1.167*** |
| | (-0.67) | | (2.83) | | (3.56) |
| ConstructionMat | 0.191*** | Road&Rail | -0.025 | ConsumerFinance | 0.445* |
| | (2.97) | | (-0.26) | | (1.99) |
| Containers&Pack | 0.136** | TransportationInfra | 0.007 | CapitalMarkets | 0.360*** |
| | (2.52) | | (0.24) | | (6.64) |
| Metals&Min | 0.383* | **ConsumerDura&Appar** | 0.289** | **Insurance** | 1.972*** |
| | (1.91) | | (2.21) | | (6.08) |
| Paper&ForestProd | 0.243*** | HouseholdDurables | 0.263*** | **Software&Serv** | -1.985*** |
| | (3.08) | | (5.14) | | (-3.74) |
| **CapitalGoods** | 1.232*** | LeisureProd | -0.022 | IT Services | -0.371*** |
| | (3.41) | | (-0.77) | | (-3.04) |
| Aerospace&Def | -0.016 | TextilesAppar&Lux | 0.047 | Software | -1.614*** |
| | (-0.04) | | (0.46) | | (-3.63) |
| BuildingProd | 0.165*** | **HealthcareEquip&Serv** | -1.254*** | TechHardware&Equip | -1.428** |
| | (3.17) | | (-3.03) | | (4.47) |
| Construction&Engin | 0.097 | HealthcareEquip&Sup | -0.792*** | CommunicationsEquip | -0.950*** |
| | (1.26) | | (-3.72) | | (-3.35) |
| ElectricalEquip | 0.207*** | HealthcareProviders&Serv | -0.378 | TechHardwareStorage&Periph | -0.505** |
| | (3.15) | | (-1.42) | | (-2.39) |
| IndustrialCongl | 0.185 | HealthcareTech | -0.084** | ElectronicEquipInstru&Compo | 0.027 |
| | (0.98) | | (-2.65) | | (0.10) |
| Machinery | 0.501*** | **PharmaBiotech&LifeSciences** | -3.209*** | **Semiconductors&SemicoEquip** | -1.762*** |
| | (4.42) | | (-3.74) | | (-2.84) |
| TradingComp&Distr | 0.094 | Biotech | -1.556** | **RealEstate** | 1.607*** |
| | (1.52) | | ( -9.61) | | (3.05) |
| **Commercial&ProfServ** | 0.253*** | Pharma | -1.43* | REITs | 1.328*** |
| | (3.31) | | (-1.67) | | (2.84) |
| CommercialServ&Sup | 0.170*** | LifeSciences | -0.222** | RealEstateManag&Dev | 0.278*** |
| | (3.01) | | (-2.35) | | (3.95) |
| ProfessionalServ | 0.083 | **Banks** | 2.400*** | | |
| | (0.82) | | (4.34) | | |
| **Transportation** | 0.007 | Banks | 1.710*** | | |
| | (0.24) | | (3.27) | | |
| AirFreight&Log | -0.284*** | Thrifts&MortgageFin | 0.690*** | | |
| | (-2.68) | | (3.35) | | |

t-statistics in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

### 5.5 Fixed Income Funds

Analyzing fixed income asset markets offers us an opportunity to observe how differences in market structure affects hedging behavior. In Table 6 we see the results of the regression specification presented in Subsection 4.2, Equation 12 and Equation 13. We see that for the high-yield bond funds, the loading on leverage risk is positive and significant, but the hedging behavior now focuses on small and medium dealers as captured by the AEM factor rather than on prime traders as captured by the HKM factor. We can also see that this hedging behavior has been ongoing throughout the sample both before and after the crisis. We do not find a significant difference between pre and post-crisis loading. These results suggest that, in the less liquid OTC based high-yield bond market, it is the smaller non-prime traders who dominate leverage provision.

In Table 7, for the universe of municipal, tax-preferred bond funds, we observe a positive and significant post-crisis loading on both AEM and HKM. These results are consistent with the changes in the municipal bond market. Before the crisis, most municipal bonds were insured by AAA-rated mono-line insurance firms. Following the collapse of these insurers during the financial crisis, the modern market exhibits a much greater diversity of risks. Our model predicts that an increase in the heterogeneity of return covariances between the assets should lead to a higher loading on the leverage risk.[16]

[16] Consistent with this hypothesis in an unreported regression we tested the loading on AAA bonds mutual funds and found no loading on either factor.

**Table 6: High Yield Bonds Funds Time Series Regressions**.

The dependent variable is $RHYBonds_t$, the excess return of the high yield mutual fund industry at time $t$. $PCrisis$ is a dummy variable dummy variable for when the quarter is later then Q3, 2008. All other controls are defined in Table 1. In each regression specification, we also include, but do not report, the market return, $PCrisis$ and interaction of all controls (including market) with $PCrisis$. Columns (2), (3), and (4) test the interaction of $PCrisis$ and the intermediary asset pricing factors. Columns (5) and (6) include only the post-crisis part of the sample. Columns (3), (4), and (6) include funding liquidity controls. $t$-statistics based on Newey-West standard errors with automatic lag selection are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) Q4-1989<t<Q4-2017 | (2) $PC$ | (3) $TED$ | (4) $BAB$ | (5) t>q32008 | (6) t>q32008 |
|---|---|---|---|---|---|---|
| $HKM_t$ | 0.010 | 0.022 | 0.009 | 0.003 | -0.025* | -0.025* |
| | (0.55) | (1.04) | (0.47) | (0.13) | (-1.92) | (-1.90) |
| $AEM_t$ | 0.059*** | 0.048* | 0.051** | 0.051** | 0.085*** | 0.087*** |
| | (2.76) | (1.84) | (2.11) | (2.17) | (6.84) | (5.87) |
| $IlliquidityR_t$ | 0.025 | 0.027 | 0.023 | 0.021 | 0.061*** | 0.061*** |
| | (1.07) | (1.17) | (1.00) | (0.92) | (3.52) | (3.53) |
| $HKM \times PCrisis$ | | -0.047 | | | | |
| | | (-1.10) | | | | |
| $AEM \times PCrisis$ | | 0.037 | | | | |
| | | (0.82) | | | | |
| $TedSpread$ | | | -0.005 | | | |
| | | | (-0.91) | | | |
| $BABR_t$ | | | | 0.030 | | -0.008 |
| | | | | (1.47) | | (-0.29) |
| Constant | -0.008*** | -0.008*** | -0.005 | -0.008*** | 0.004*** | 0.004*** |
| | (-3.97) | (-3.90) | (-1.31) | (-4.12) | (3.70) | (2.62) |
| N | 111 | 111 | 111 | 111 | 36 | 36 |
| $R^2$ | 0.91 | 0.91 | 0.91 | 0.91 | 0.99 | 0.99 |
| Market Index | YES | YES | YES | YES | YES | YES |
| Treasuries Index | YES | YES | YES | YES | YES | YES |
| High Yield Bonds Index | YES | YES | YES | YES | YES | YES |
| Post-Crisis Controls | YES | YES | YES | YES | YES | YES |

t-statistics in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 7: Municipal Bond Funds Time Series Regressions**.

The dependent variable is $RMBonds_t$, the excess return of the municipal bond mutual fund industry at time $t$. $PCrisis$ is a dummy variable for when the quarter is later then Q3, 2008. All other controls are defined in Table 1. In each regression specifications, we also include, but not report, the market return, $PCrisis$ and interaction of all controls (including market) with $PCrisis$. Columns (2), (3), and (4) test the interaction of $PCrisis$ and the intermediary asset pricing factors. Columns (5) and (6) include only the post-crisis part of the sample. Columns (3), (4), and (6) include funding liquidity controls. $t$-statistics based on Newey-West standard errors with automatic lag selection are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Q4-1989<t<Q4-2017 | $PC$ | $TED$ | $BAB$ | t>Q3-2008 | t>Q3-2008 |
| $HKM_t$ | 0.006 | 0.000 | -0.000 | -0.009 | 0.020* | 0.022** |
| | (0.61) | (0.02) | (-0.00) | (-0.83) | (1.69) | (1.99) |
| $AEM_t$ | 0.023** | 0.006 | -0.008 | -0.006 | 0.060*** | 0.044*** |
| | (2.14) | (0.57) | (-0.78) | (-0.56) | (5.08) | (3.38) |
| $IlliquidityR_t$ | 0.010 | 0.006 | 0.005 | 0.003 | 0.027* | 0.028** |
| | (0.90) | (0.59) | (0.49) | (0.32) | (1.81) | (2.17) |
| $HKM \times PCrisis$ | | 0.020 | 0.019 | 0.030* | | |
| | | (1.06) | (1.13) | (1.66) | | |
| $AEM \times PCrisis$ | | 0.054** | 0.019 | 0.050** | | |
| | | (2.31) | (0.76) | (2.14) | | |
| $TedSpread$ | | | -0.015*** | | | |
| | | | (-5.32) | | | |
| $BABR_t$ | | | | 0.037*** | | 0.061*** |
| | | | | (3.13) | | (2.89) |
| Constant | -0.011*** | -0.010*** | -0.002 | -0.011*** | -0.001 | -0.003*** |
| | (-8.09) | (-7.81) | (-1.23) | (-8.95) | (-1.01) | (-2.90) |
| N | 111 | 111 | 111 | 111 | 36 | 36 |
| $R^2$ | 0.90 | 0.90 | 0.93 | 0.91 | 0.97 | 0.97 |
| Market Index | YES | YES | YES | YES | YES | YES |
| Treasuries Index | YES | YES | YES | YES | YES | YES |
| Municipal Bonds Index | YES | YES | YES | YES | YES | YES |
| Post-Crisis Controls | YES | YES | YES | YES | YES | YES |

t-statistics in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

# 6 Conclusion

How does leverage affect the interplay between different investors? Our work shows that financial markets act as a risk pooling mechanism, allowing leveraged and unleveraged investors to hedge the opposite risks they incur from the unknown future availability of leverage on their investment opportunities. Hedge funds choose portfolios that load negatively on the factor while mutual funds choose portfolios that load negatively on the factor. This hedging activity intensifies when the supply of leverage is expected to be more volatile in the future.

By analyzing these interactions, we are establishing that intermediary asset pricing is not just a study of a risk and a pricing factor but a study of how the supply and demand for leverage affect investor behavior. This implies that IPFs should be used not just as imputes for estimating prices but, alongside our own FHedge measure, as proxies for market conditions for wide range of financial research. Furthermore, we believe that the methodology of analyzing how different types of investors react differently to the same risks could be applied in future work to test other asset pricing models which predict cross-sectional differences in investor behavior.

Finally, our work presents evidence of how the financial crisis increased market awareness of systemic risks, leading to changes in investment behavior. The sharp post-crisis increase in the loading on intermediary factors implies that the crisis created a new awareness in leveraged investors and leverage providers on the need to hedge leverage risk. We believe that this offers opportunities for future research on other ways in which investor preferences changed following the crisis.

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# Appendix A Factor Loading Placebo Test

In this section we present the results of our placebo tests using the Fama-Mcbeth factors and the momentum factor. For each factor we recreated our time series regressions on the returns of equity mutual fund industry. For each factor we recreated the regressions once for the entire sample and once including an interaction variable with a post-crisis dummy variable. We did not find a positive significant coefficient in any of our placebo tests. This is contrast with our results for the HKM factor. This seems to indicate that the HKM factor is unique for being a factor that mutual funds are loading on positively. This is consistent with hedge fund not being willing to load negatively on other factors which are not viewed as unwanted risk.

**Table 8: Placebo factor loading regressions**.

The dependent variable is $REquity_t$, the excess return of the equity mutual fund industry at time $t$. $PCrisis$ is a dummy variable if $t > Q3 - 2008$. All other controls are defined at table 1. In each regression specifications we also include, but not reported, the market returns, $PCrisis$ and interaction of all controls (including market) with $PCrisis$. Columns (1) and (2) test the loading on the Value factor. Columns (3) and (4) test the loading on the Size factor. Columns (5) and (6) test the loading on the momentum factor. Columns (2), (4) and (6) include the interaction of the factors with the $PCrisis$ dummy. $t$-statistics based on Newey-West standard errors with automatic lag selection are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) $HML$ | (2) $HMLPC$ | (3) $SMB$ | (4) $SMBPC$ | (5) $MOM$ | (6) $MOMPC$ |
|---|---|---|---|---|---|---|
| $HML_t$ | -0.005 | 0.010 | | | | |
| | (-0.20) | (0.34) | | | | |
| $HMLPC$ | | -0.060 | | | | |
| | | (-0.97) | | | | |
| $SMB_t$ | | | 0.035 | 0.027 | | |
| | | | (1.10) | (0.81) | | |
| $SMBC$ | | | | 0.061 | | |
| | | | | (0.64) | | |
| $MOM_t$ | | | | | -0.019 | 0.013 |
| | | | | | (-1.01) | (0.57) |
| $MOMPC$ | | | | | | -0.092** |
| | | | | | | (-2.57) |
| Constant | -0.003 | -0.003 | -0.003 | -0.003* | -0.002 | -0.003* |
| | (-1.39) | (-1.57) | (-1.60) | (-1.65) | (-1.21) | (-1.79) |
| N | 111 | 111 | 111 | 111 | 111 | 111 |
| $R^2$ | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| Mkt Contr | YES | YES | YES | YES | YES | YES |
| PC Contr | YES | YES | YES | YES | YES | YES |
| Illiq Contr | YES | YES | YES | YES | YES | YES |

t-statistics in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

# Appendix B AAA Bond Factor Loading

In this section we present the results of the factor loading of the AAA bond mutual fund industry. We did not find a significant loading on either of the leverage factors for the industry. This is inline with our model, as the low heterogeneity between the AAA asset would make any sort of hedging activity in this asset class difficult.

**Table 9: AAA Bonds Funds Time Series Regressions**.

The dependent variable is $RAAA_t$, the excess return of the AAA bond mutual fund industry at time $t$. $PCrisis$ is a dummy variable if $t > Q3 - 2008$. All other controls are defined at table 1. In each regression specifications we also include, but not reported, the market returns, $PCrisis$ and interaction of all controls (including market) with $PCrisis$. Columns (2) (3) and (4) test the interaction of $PCrisis$ and the intermediary asset pricing factors. Columns (5) (6) include only the post crisis part of the sample. Columns (3) (4) and (6) include funding liquidity controls. $t$-statistics based on Newey-West standard errors with automatic lag selection are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Q4-1989<t<Q4-2017 | $PC$ | $TED$ | $BAB$ | t>Q3-2008 | t>Q3-2008 |
| $HKM_t$ | 0.012 | 0.005 | 0.003 | -0.005 | 0.022 | 0.022 |
| | (1.06) | (0.38) | (0.21) | (-0.37) | (1.02) | (0.99) |
| $AEM_t$ | 0.017 | 0.006 | -0.003 | -0.005 | 0.039 | 0.022 |
| | (1.29) | (0.40) | (-0.20) | (-0.34) | (1.47) | (0.74) |
| $IlliquidityR_t$ | 0.018 | 0.015 | 0.018 | 0.015 | 0.081*** | 0.078*** |
| | (1.28) | (1.05) | (1.27) | (1.07) | (2.68) | (2.61) |
| $HKM \times PCrisis$ | | 0.017 | 0.016 | 0.027 | | |
| | | (0.71) | (0.69) | (1.13) | | |
| $AEM \times PCrisis$ | | 0.033 | 0.069* | 0.028 | | |
| | | (1.14) | (1.84) | (0.86) | | |
| $BABR_t$ | | | | 0.031** | | 0.048 |
| | | | | (2.12) | | (1.06) |
| Constant | -0.008*** | -0.008*** | -0.003 | -0.008*** | 0.003 | 0.001 |
| | (-5.03) | (-5.27) | (-1.16) | (-5.14) | (1.40) | (0.33) |
| N | 111 | 111 | 111 | 111 | 36 | 36 |
| $R^2$ | 0.75 | 0.75 | 0.77 | 0.77 | 0.65 | 0.66 |
| Market Index | YES | YES | YES | YES | YES | YES |
| Treasuries Index | YES | YES | YES | YES | YES | YES |
| Post-Crisis Controls | YES | YES | YES | YES | YES | YES |

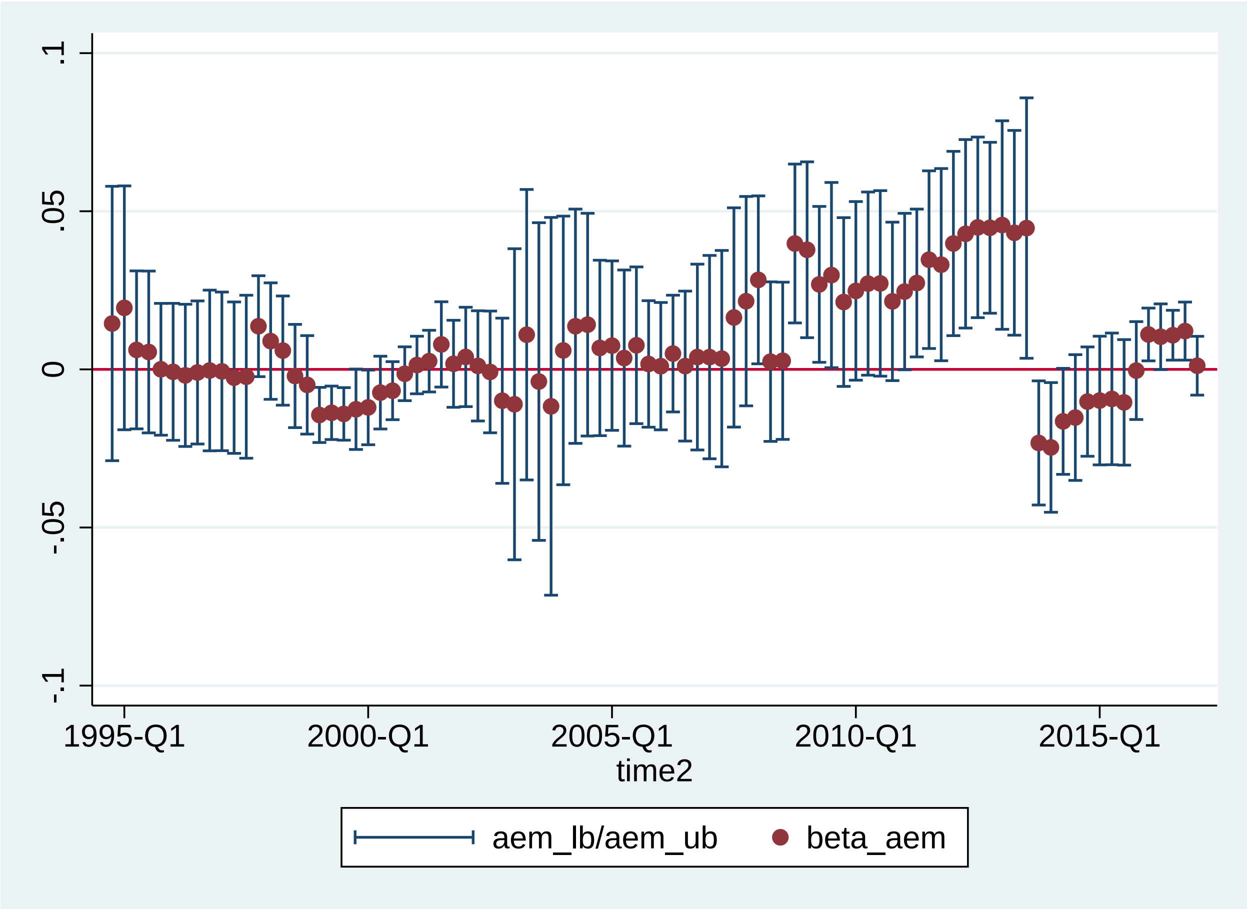
t-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## Appendix C Fixed Income Loading Time Series

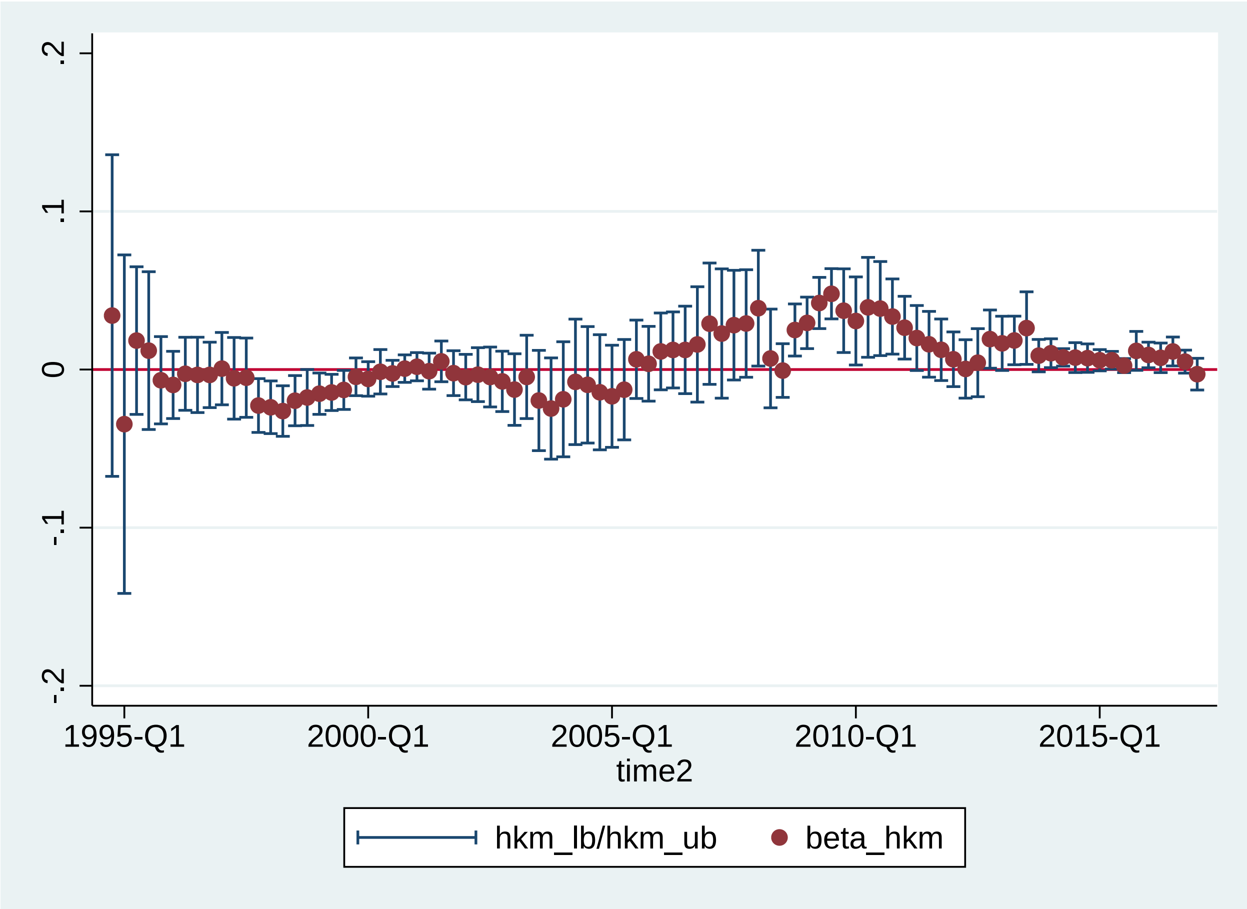
In this section we include results of the rolling window panel regressions for the municipal bond fund industry and the high-yield bond fund industry. Each point estimate is the HKM beta from a 5 years, rolling window panel regression of equity mutual funds returns on the HKM, AEM, Pastor-Stambaugh and market factor. We also controlled for the mutual funds size, expense ratio and fund fixed effects. Results are weighted by size. SE are clustered by fund and time.

**Figure 4: AEM Factor Loading Rolling Regressions: Municipal Bonds Funds**



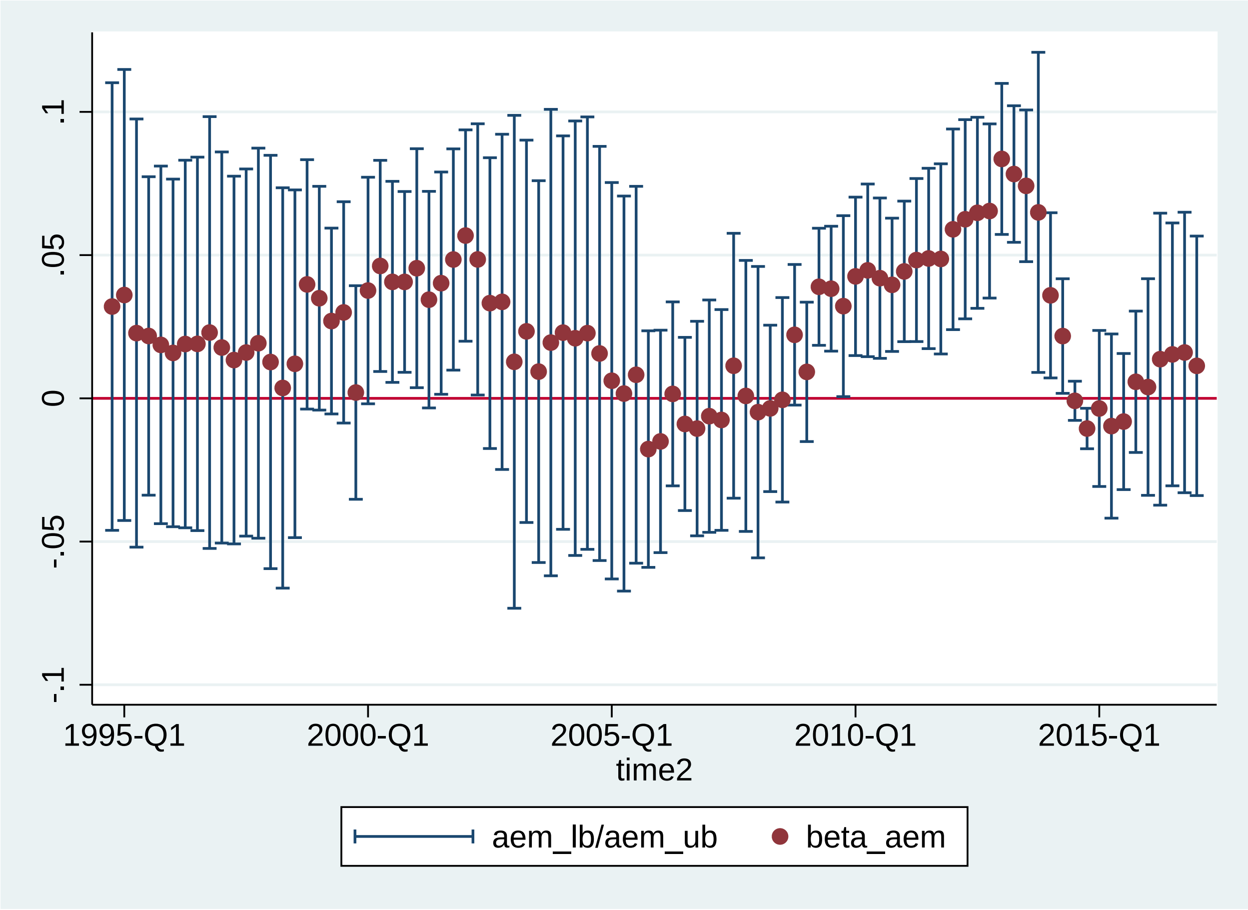

This figure shows the loading of the municipal mutual fund industry on the AEM factor. Each point estimate is the HKM beta from a panel regression of equity mutual funds returns on the HKM, AEM, Pastor-Stambaugh and market factor. Each regressions uses a 5 years rolling window. We also controlled for the mutual funds size, expense ratio and fund fixed effects. Results are weighted by size. SE are clustered by fund and time.

**Figure 5: HKM Factor Loading Rolling Regressions: Municipal Bonds Funds**



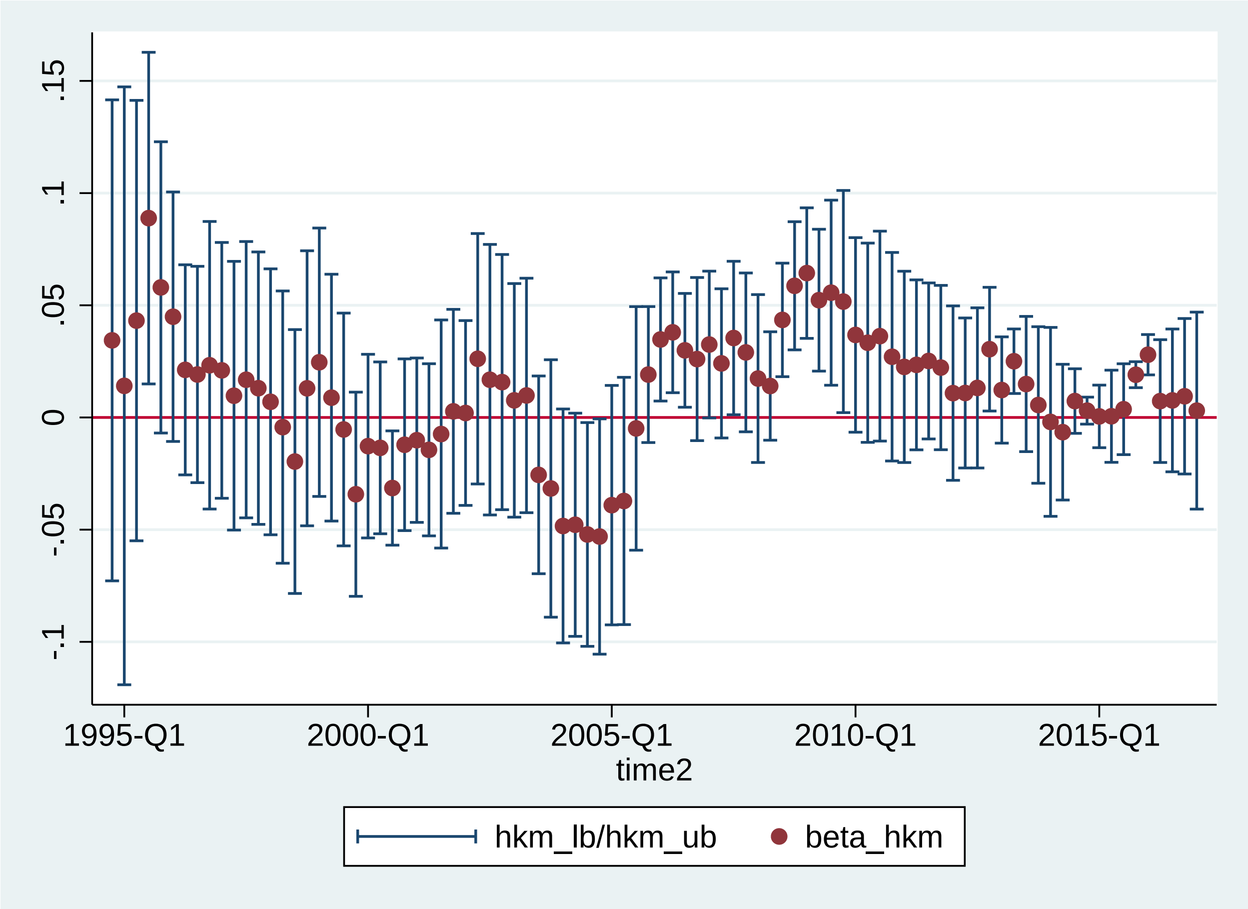

This figure shows the loading of the municipal mutual fund industry on the HKM factor. Each point estimate is the HKM beta from a panel regression of equity mutual funds returns on the HKM, AEM, Pastor-Stambaugh and market factor. Each regressions uses a 5 years rolling window. We also controlled for the mutual funds size, expense ratio and fund fixed effects. Results are weighted by size. SE are clustered by fund and time.

**Figure 6: AEM Factor Loading Rolling Regressions: High-Yield Bonds Funds**




This figure shows the loading of the municipal mutual fund industry on the AEM factor. Each point estimate is the HKM beta from a panel regression of equity mutual funds returns on the HKM, AEM, Pastor-Stambaugh and market factor. Each regressions uses a 5 years rolling window. We also controlled for the mutual funds size, expense ratio and fund fixed effects. Results are weighted by size. SE are clustered by fund and time.

**Figure 7: HKM Factor Loading Rolling Regressions: High-Yield Bonds Funds**




This figure shows the loading of the municipal mutual fund industry on the HKM factor. Each point estimate is the HKM beta from a panel regression of equity mutual funds returns on the HKM, AEM, Pastor-Stambaugh and market factor. Each regressions uses a 5 years rolling window. We also controlled for the mutual funds size, expense ratio and fund fixed effects. Results are weighted by size. SE are clustered by fund and time.