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Dahlquist, Magnus; Rottke, S.R.; Sokolovski, Valeri; Sverdrup, Erik

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Financial Intermediary Risk and the Cross-section of Hedge-fund Returns

Magnus Dahlquist Simon Rottke Valeri Sokolovski Erik Sverdrup*

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Abstract

We find that systematic financial intermediary risk, measured by the covariation between fund returns and shocks to the equity capital ratio of key financial intermediaries – New York Federal Reserve *Primary Dealers* – is a strong determinant of the cross-section of hedge fund returns. A portfolio of hedge funds with high financial intermediary risk exposure outperforms, on average, a low-exposure portfolio by approximately 7% per year on a risk-adjusted basis. This positive relationship remains robust after controlling for a comprehensive set of fund characteristics and other risk factors known to influence the cross-section of hedge fund returns.

Keywords: Intermediary risk, systematic risk, hedge funds.
JEL codes: G12, G23, G24.

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1 Introduction

Recent research finds that factors proxying for shocks to the intermediaries' aggregate risk-bearing capacity can capture the cross-section of expected returns across multiple asset classes (see, e.g., Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017; Du, Hébert, and Huber, 2023). Notably, intermediary health seems to matter relatively more for exotic assets that households are unlikely to hold directly (Haddad and Muir, 2021). There is also some evidence suggesting that systematic financial intermediary risk matters for hedge fund returns; however, to the best of our knowledge, no thorough evaluation has yet been undertaken.[1] In this paper, we evaluate systematic intermediary risk in the cross-section of hedge fund returns to fill this gap in the literature and provide a comprehensive answer to whether financial intermediary risk plays a significant role in hedge fund returns.

We conduct our analysis using a union of five leading commercial databases, comprising over 16,000 individual hedge funds, covering the period from January 2000 to June 2021. As a measure of systematic financial intermediary risk, we use the financial intermediary risk factor from He et al. (2017) (hereafter, HKM), defined as shocks to the equity capital ratio of New York Federal Reserve Primary Dealers (a small group of systemically important banks). We adopt this measure to align with the existing literature and because (i) it has been shown to be priced across multiple asset classes, (ii) it is available at a monthly frequency, and (iii) there is a clear rationale to believe that shocks to these key financial intermediaries would significantly impact hedge funds. Primary Dealers, who serve as the largest prime brokers, typically work closely with hedge funds and operate in the same markets that hedge funds do (see, e.g., Aragon and Strahan, 2012; Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel, 2020; Dahlquist, Rottke, and Sokolovski, 2025).

We begin by examining portfolios of hedge funds sorted based on their loading on the

[1]For example, Chen, Joslin, and Ni (2018) find that the tightening of the intermediary constraints predicts higher future excess returns for a number of financial assets including an aggregate hedge fund portfolio. Similarly, Haddad and Muir (2021) find that shocks to intermediary health predict the quarterly returns of several hedge fund indexes.

financial intermediary risk factor. A portfolio of hedge funds with relatively high intermediary risk exposure delivers an annual excess return and a Fung and Hsieh (2004) seven-factor alpha that are, on average, approximately 5.8% and 7.0% higher, respectively, than those of a portfolio of low-loading funds. Moreover, the performance spread in both returns and alphas between the high-intermediary-risk hedge fund portfolio and the low-intermediary-risk portfolio remains stable over time and displays economically reasonable time series properties. Notably, we observe that during months with the most negative (bottom decile) abnormal intermediary capital shock realizations, the funds with the lowest loading on the intermediary factor significantly outperform those with the highest. Conversely, during months with the most positive abnormal intermediary capital shock realizations, this effect is reversed. This suggests that funds exposed to financial intermediary risk are indeed rewarded for bearing that risk.

Next, we conduct cross-sectional asset pricing regression tests and find that the covariation between fund returns and the HKM financial intermediary factor is a strong determinant of the cross-section of hedge fund returns. These results are robust to controlling for a comprehensive set of fund characteristics that the literature has shown to influence the cross-section of hedge fund returns, including hedge fund styles, size, age, lockup provisions, redemption periods, the existence of high-water marks, past fund performance, and management and incentive fees. We find an annualized risk price of approximately 5.7%, which is consistent with the mean excess return observed in our analysis of hedge fund portfolios sorted by financial intermediary risk.

Lastly, we perform a battery of robustness tests. We examine different samples and time periods, and separately analyze cross-sections of hedge funds of specific styles, consistently finding similar results across different cases. Using a double-sort procedure, we also show that accounting for other factors – such as the liquidity factor of Pástor and Stambaugh (2003), the correlation factor of Buraschi, Kosowski, and Trojani (2013), the macroeconomic uncertainty factor of Bali, Brown, and Caglayan (2014), the noise factor

of Hu, Pan, and Wang (2013), the option-based intermediary constraint factor of Chen, Joslin, and Ni (2019), the jump risk factor of Cremers, Halling, and Weinbaum (2015), and the tail risk factor of Agarwal, Ruenzi, and Weigert (2017) – preserves the cross-sectional spread in returns of the intermediary-factor-sorted hedge fund portfolios.

Our work contributes to two strands of the literature. First, we contribute to the literature on financial intermediary asset pricing (see He and Krishnamurthy, 2018, for a survey). In particular, Adrian et al. (2014) show that a factor constructed from shocks to the leverage of US securities broker-dealers can price the cross-section of US bond and equity portfolios. Subsequently, HKM find that a pricing factor constructed from the equity ratios of a small group of key intermediaries, the Primary Dealers, can price a wide cross-section of assets in many different markets. However, neither of these studies consider hedge funds. Intermediary health should matter relatively more for exotic assets like hedge funds that households rarely hold directly (Haddad and Muir, 2021). As one of their tests, Haddad and Muir (2021) examine the predictive power of shocks to financial intermediary health for hedge fund index returns, finding significant predictability that is stronger for hedge fund index returns than for equity returns. This evidence suggests that financial intermediary risk is important for hedge funds. We expand on that analysis by analyzing a large panel of individual hedge funds, conducting cross-sectional asset pricing tests, and controlling for key characteristics and alternative factors commonly considered in the hedge fund literature. Consequently, our cross-sectional asset pricing results highlight the external validity of intermediary pricing, demonstrating that intermediary factors, which are effective in explaining the cross-section of base assets, also influence the broader universe of hedge fund returns.

Second, we contribute to the large literature on the drivers of hedge fund returns. Hedge funds are dynamically managed portfolios of securities of multiple asset classes. Partly because of this, established factor models from other asset classes have struggled to explain hedge fund returns in both the time series and in the cross-section. This spawned

the development of hedge-fund-specific factor models (see, e.g., Agarwal and Naik, 2004; Fung and Hsieh, 1997, 2001, 2004), among which the Fung-Hsieh model is most widely used and captures the time series of hedge fund returns. However, none of the Fung-Hsieh factor loadings generate a significant return spread in the cross-section (Sadka, 2010). Several additional factors have been proposed to explain the cross-section of hedge fund returns, with liquidity and market dislocation factors being prominent (see, e.g., Agarwal et al., 2017; Bali, Brown, and Caglayan, 2012; Bali et al., 2014; Buraschi et al., 2013; Cao, Chen, Liang, and Lo, 2013; Hu et al., 2013; Klingler, 2022; Sadka, 2010; Teo, 2011). The literature, however, has not converged on the relevant systematic factors. Our results show that systematic financial intermediary risk is a key driver of hedge fund returns. This helps in the reconciliation of hedge fund performance with a theoretically motivated factor found to be important in other asset classes. Given the typically limited success of models from other asset classes in explaining the cross-section of hedge fund returns, aligning hedge fund returns with a risk factor shown to be priced in other asset classes marks progress in determining the key systematic risks.

2 Data

2.1 Hedge fund data

We collect monthly returns, AUM, and hedge fund characteristics from five major commercial databases: BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS. By merging these data sources, we construct a comprehensive database that includes all hedge funds (both active and defunct) listed in any of the five databases.[2] Our sample period runs from January 2000 to June 2021.[3]

Consistent with established practices in the literature, we apply several filters to the

[2]The specifics of the merging process are detailed in Dahlquist et al. (2025).

[3]Due to inconsistent coverage, we exclude data from before 2000, in line with Teo (2009).

data. We focus solely on hedge funds that report monthly net-of-fees returns, excluding all fund-of-funds. Following the methodology outlined by Almeida, Ardison, and Garcia (2020), we remove funds with unusual return patterns, such as repeated identical returns over extended periods or recurring 'blocks' of returns (see, e.g., Straumann, 2009; Bollen and Pool, 2012). Funds that do not report key information, such as their currency, strategy, or AUM, are also excluded, as are those with an AUM below $1 million. For funds with multiple share classes, we retain only one share class per fund while aggregating their AUMs. Additionally, we require that each fund in the sample has at least 24 months of reported returns during the sample period. After applying these filters, our final dataset consists of a panel of 16,160 unique hedge funds.

Table 1 presents the summary statistics for hedge fund excess returns and AUMs in our dataset, all expressed in USD. We provide statistics for the full sample, various sub-periods, and across different hedge fund styles. Each fund in the sample is categorized into one of the following 12 styles: CTA, Emerging Markets, Event Driven, Global Macro, Long Only, Long Short, Market Neutral, Multi Strategy, Others, Relative Value, Sector, and Short Bias.[4] We report the cross-sectional averages of each fund's monthly excess returns and the standard deviations of these returns, providing a representation of typical fund performance. Similarly, AUM statistics (mean, median, and the 25^{th} and 75^{th} percentiles) reflect the time-series average of the monthly cross-sectional data, illustrating the typical AUM distribution across funds. We also report the cross-sectional standard deviation of the average excess returns.

The average hedge fund in our sample delivers an annualized return of 5.06% with a standard deviation of 15.04%, though performance varies across funds, as indicated by a cross-sectional standard deviation of 10.91%. There is also substantial variation across time: the best average return (standard deviation) of 9.02% (12.72%) is recorded during

[4]Hedge fund databases use different terminologies for investment styles. To maintain consistency with the existing literature, we have adjusted the native database classifications to match the 12 categories proposed by Kosowski, Joenväärä, and Tolonen (2016).

the 2000–2007 period. The Great Financial Crisis period (2008–2009) is associated with the poorest performance, with an average return (standard deviation) of 2.43% (21.22%). There is also a meaningful variation in average performance across hedge fund styles. For example, hedge funds classified as Market Neutral have slightly lower average monthly returns and standard deviations (2.71% and 11.04%, respectively) than hedge funds of other styles. There are notable size differences among hedge funds in our sample, with most funds being relatively small. The median fund has an AUM of $47 million, with the interquartile range between $12 million and $181 million, showing only modest variation across time and styles. However, the presence of several large funds pushes the average AUM up to $348 million.

Hedge fund databases also offer information on various static fund characteristics, such as management and incentive fees, lock-up and redemption terms, minimum investment requirements, and whether a high watermark provision is in place. We include these characteristics as control variables in our analysis.

2.2 Factor data

The seven Fung and Hsieh (2004) factors are from Datastream and David A. Hsieh's Hedge Fund Data Library. The risk-free rate and the market return are from Kenneth R. French's Data Library. Credit Suisse Hedge Fund Index is sourced from the Credit Suisse website. The HKM intermediary factor; Pástor and Stambaugh (2003) liquidity factor; the noise factor of Hu et al. (2013); Bali et al. (2014) uncertainty factor; and the Agarwal et al. (2017) tail risk factor are sourced from the authors' websites. The correlation factor of Buraschi et al. (2013) and the jump risk factor of Cremers et al. (2015) are obtained directly from the authors.

3 Financial intermediary risk in the cross-section of hedge funds

In this section, we formally investigate the effect of systematic financial intermediary risk on the cross-section of hedge funds. As a proxy for financial intermediary risk we use the HKM factor, which we denote as FI.[5]

3.1 Intermediary-beta-sorted portfolios

To evaluate the effect of financial intermediary risk on the cross-section of hedge fund returns, we begin with the portfolio-based approach commonly used in the literature (see, e.g., Sadka, 2010; Teo, 2011; Hu et al., 2013; Bali et al., 2014). Specifically, every month we sort all the hedge funds in our sample into 10 portfolios based on their 24-month rolling financial intermediary factor betas. For each hedge fund i, we estimate the rolling FI beta in month t using the following regression:

$$r_{i,t} = a_{i,t} + \beta_{i,t}^{\mathrm{FI}} \mathrm{FI}_t + \beta_{i,t}^{\mathrm{M}} r_t^{\mathrm{M}} + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the month t excess returns for fund i, and FI_t and r_t^{M} are the month t realizations of FI and the aggregate stock market portfolio, respectively. Regression (1) corresponds to the theoretically-motivated two-factor model that HKM consider. After having monthly beta estimates, $\hat{\beta}_{i,t}^{\mathrm{FI}}$, we form 10 equal-weighted portfolios of hedge funds based on them. Hedge funds with the lowest FI betas are allocated to Portfolio 1, and the funds with the highest FI betas are allocated to Portfolio 10. This procedure gives us 10 time series of monthly hedge fund portfolio returns. We then compute the post-ranking betas of each of the ten portfolios by regressing the portfolio returns on the two factors in regression (1).

Table 2 reports the average monthly excess returns, CAPM alphas and Fung and Hsieh

[5]HKM factor is defined as innovations in the intermediary capital ratio. The ratio is constructed by dividing the total market equity of primary dealers by their total assets, which is the sum of total market equity and total book debt.

(2004) seven-factor alphas for our 10 hedge fund portfolios. It also reports the post-sort and pre-sort betas. The pre-ranking beta of a portfolio is its average fund level rolling beta. The high-FI-beta portfolio (Portfolio 10) has the highest average return or alpha, and the low-FI-beta portfolio (Portfolio 1) has the lowest. The hypothetical strategy of going long Portfolio 10 and going short Portfolio 1 yields an annualized excess return of 5.76% (t-stat = 2.26) or an annual CAPM and Fung and Hsieh (2004) alpha of 6.36% (t-stat = 2.13) and 6.96% (t-stat = 2.23), respectively.

To interpret this positive spread in the average returns as compensation for risk, we show that these portfolios exhibit a positive spread in their betas on the intermediary risk factor over the same period used to compute the alpha. The post-ranking betas increase monotonically from Portfolio 1 to Portfolio 10, and there is a significant difference of 0.27 (t-stat = 4.22) between the FI betas of Portfolio 10 and Portfolio 1. These results are in line with the financial intermediary risk being a determinant of the cross-section of hedge fund returns.

We provide an intuitive illustration of financial intermediary risk in practice. We examine the 20 largest positive and negative realizations of the FI factor (orthogonalized with respect to the market return) and calculate the return on the two decile portfolios with the highest and lowest loading (Portfolios 1 and 10, respectively). The two panels of Figure 3 display the average returns for the two portfolios (also orthogonalized with respect to the market return) during the extreme negative and positive realizations of the FI factor. The portfolio with low intermediary beta yields a positive market-risk-adjusted return during extreme negative shocks to the FI factor, while the portfolio with high beta earns a negative risk-adjusted return during these periods. The direction is reversed in the periods experiencing large positive shocks to the FI factor. This provides further evidence that the spread in average hedge fund returns of the FI-sorted portfolios is likely driven by exposure to intermediary risk.

Lastly, we examine the performance of intermediary-factor-sorted hedge fund portfolios over time. Panels (a) and (b) of Figure 1 indicate that the hypothetical long-short hedge fund portfolio consistently generated a positive return and alpha spread in most years of the sample. Although the portfolio experienced a significant downturn during the COVID crisis, it demonstrated considerable recovery by the end of the sample period, as measured by the 7-factor alpha. We also plot the aggregate Credit Suisse Hedge Fund Index in the same figure for reference. The long-short FI-sorted portfolio outperforms the aggregate hedge fund index in both returns and, more notably, in terms of 7-factor alpha. Although the long-short hedge fund portfolio is not directly tradable, the comparison with the aggregate hedge fund index nonetheless highlights the economic significance of the reported spread. Panels (c) and (d) of Figure 1 further reveal that the outperformance was alternately driven by either the long or the short leg of the portfolio.

3.2 Cross-sectional regressions

While we do find that that there is a positive relationship between exposure to intermediary risk and average returns, this does not rule out the influence of known determinants of expected hedge fund returns in the cross-section. In this subsection, we evaluate whether financial intermediary risk exposure is robust to controlling for various fund characteristics. To this end, we estimate Fama and MacBeth (1973) regressions of hedge fund excess returns on FI beta and additional controls by running the following cross-sectional regression for every month t:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{\text{FI},t}\hat{\beta}^{\text{FI}}_{i,t} + \lambda_{\text{M},t}\hat{\beta}^{\text{M}}_{i,t} + c_t' X_{i,t} + \varepsilon_{i,t+1}, \tag{2}$$

where $r_{i,t+1}$ are the month $t+1$ excess returns for fund i, $\lambda_{0,t}$ is the intercept, $\hat{\beta}^{\text{FI}}_{i,t}$ is the month t FI beta of fund i, $\hat{\beta}^{\text{M}}_{i,t}$ is the month t market beta of fund i, $X_{i,t}$ is a vector of controls, and $\varepsilon_{i,t+1}$ is an error term. The betas are estimated rolling betas, as in the previous subsection. The controls are standard in the literature and include the fund's

excess return for month t, age, AUM, management fee, incentive fee, high watermark (an indicator variable that equals one if fund i has a high watermark provision and zero otherwise), lockup (an indicator variable that equals one if fund i has a lockup provision and zero otherwise), mandated redemption notice period, and minimal investment in the fund. Controls also include hedge fund style dummies. The factor premiums are estimated as the time series averages of $\hat{\lambda}_{\mathrm{FI},t}$ and $\hat{\lambda}_{\mathrm{M},t}$.

Specifications I–IV of Table 3 report the average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regression in (2). The standard errors in parentheses are adjusted for autocorrelation and heteroskedasticity as in Newey and West (1987) (the lag length is selected automatically using the Newey and West (1994) procedure). The estimated FI risk premium is positive and significant in all the specifications. In specification IV, with all the covariates, the point estimate of the risk premium is 0.48% (5.76% annualized), significant at the 5% level. Additionally, Figure 2 shows the time series of cumulative values for the financial intermediary premium, estimated following the method of Fama and MacBeth (1973) using specification IV (which includes all controls) as reported in Table 3. As shown in the figure, the cumulative premium is substantially positive and remains relatively stable over time.

The coefficients on the controls are of the signs as reported by the existing literature, and most are statistically significant. Specifically, the estimated coefficient on the previous month's hedge fund return is positive and strongly statistically significant, consistent with hedge fund returns being autocorrelated (see, e.g., Getmansky, Lo, and Makarov, 2004). The estimated coefficients on a fund's AUM and age are both negative, with the one on age being significant, in line with the observation that smaller, younger funds tend to have higher average returns than larger, more established funds (see, e.g., Aggarwal and Jorion, 2010). The coefficients on management and incentive fee are positive and significant, as in Teo (2009). The coefficient on the redemption notice period is positive and significant, which is in line with Aragon (2007), who finds that proxies for share restrictions (such

as lockups, redemption notice periods, and minimum investment amounts) are positively related to average hedge fund returns. The high watermark indicator is positive and statistically significant, as in Agarwal, Daniel, and Naik (2009).

In sum, we find that there is a significant, positive relationship between exposure to intermediary risk and individual hedge funds' average returns, even after controlling for a large set of hedge fund characteristics known to predict returns.

4 Robustness

In this section, we conduct several robustness tests of our main empirical results.

4.1 Sub-sample analysis

We replicate the portfolio analysis from Section 3.1 across several sub-samples and all major hedge fund styles. Notably, the initial version of this paper was completed in 2017. At that time, our sample period ended in June 2017, and we had access to only a single hedge fund database, Eurekahedge. This gives us two natural sub-samples to analyze: the original sample period ending in June 2017, and a sample that focuses solely on the Eurekahedge database but covers the entire sample period. Table 4 presents the results, with the first row repeating the full sample results from Table 2. In line with the patterns observed in Figure 1 which highlighted the poor performance of FI-sorted portfolios during the COVID crisis we observe higher spread in the sample ending in June 2017, with the annualized 7-factor alpha of 8.4% (t-stat = 3.01). Reassuringly, we obtain similar results when restricting our analysis to the Eurekahedge database, as used in the earlier version of the paper, with the point estimate of the 7-factor alpha matching that of our main sample. Given that the timing of this research allowed for a natural out-of-sample evaluation, we have a high degree of confidence in the robustness and consistency of our main findings. Additionally, to ensure that our results are not unduly influenced by smaller hedge funds,

we also reanalyze samples where hedge fund AUM is restricted to being above $20, $50, and $100 million, respectively. We observe very little effect on the spread in returns or alphas with these additional AUM filters.

We also replicate the portfolio analysis across all major hedge fund styles, where we can allocate at least five funds to both the long and short legs of the portfolio, respectively, each month. Results are presented in the bottom panel of Table 4. We find statistically significant spreads in both raw and abnormal returns for the Long Short, Relative Value, and Event Driven hedge fund styles. Additionally, the Emerging Market style shows a spread in raw and abnormal returns similar to the full sample (0.52 vs. 0.48), though it is not statistically significant. We attribute this to lower statistical power, as there are comparatively fewer Emerging Market funds (with an average cross-section of 155 funds, resulting in only 16 funds per portfolio, on average) compared to, for example, the Long Short style (167 funds per portfolio). We do not observe a significant spread in returns for the CTA and Global Macro styles. Specifically, for the CTA style, this result is intuitive, as there is no significant spread in ex-post FI betas among these hedge funds. Most likely, the high-frequency, dynamic trend-following strategies deployed by CTAs rarely maintain exposure to any single factor long enough to generate a meaningful spread in returns. It is well-documented that it is difficult to explain variation in the ex-post gross returns of CTAs (Bhardwaj, Gorton, and Rouwenhorst, 2014). We suspect that the lack of a significant return spread among Global Macro hedge funds may be due to a similar reason. Global Macro hedge funds are often known for trading across a large number of asset classes and frequently changing their positions. Such dynamic strategies likely make it difficult to establish a stable spread in returns.

Lastly, we repeat the analysis using the traded version of the HKM factor (constructed as the value-weighted return of a portfolio of Primary Dealers) and find results very similar to those obtained using the original non-traded HKM factor. Overall, the consistency of our findings across different sub-samples, time periods, and hedge fund styles underscores

the robustness of our results, providing further evidence that financial intermediary risk plays a role in explaining the cross-section of hedge fund returns.

4.2 Alternative factors

In this subsection we check whether the cross-sectional spread in returns and alphas of the FI-factor-sorted hedge fund portfolios is preserved in the presence of factors considered in the literature.

We follow the procedure outlined in Ang, Hodrick, Xing, and Zhang (2006) to account for alternative factors. For example, to control for liquidity factor of Pástor and Stambaugh (2003), we first sort funds into five quintiles based on their historical Pástor and Stambaugh (2003) liquidity betas. Within each quintile, we then sort each fund into five portfolios sorted on their historical FI betas (all porfolios are equal-weighted and rebalanced monthly). The five FI beta-sorted portfolios are finally averaged over each of the Pástor and Stambaugh (2003) liquidity sorted portfolios. The same procedure is performed for the other factors.

Table 5 presents the Fung and Hsieh (2004) alphas and average monthly returns for the five portfolios obtained from controlling for the various factors. We note that the sample periods vary depending on the availability of alternative factors, with the specific sample periods indicated in Table 5.

When controlling for the Pástor and Stambaugh (2003) liquidity factor, the annualized spread in returns and alphas are lower compared to the benchmark case, standing at 3.36% and 3.84%, respectively (t-stats = 2.21 and 2.19). These results suggest that the FI factor is related to liquidity risk, which is expected given that financial intermediaries are key suppliers of liquidity in the economy and that there is a well-established correlation between financial intermediary health and liquidity (see, e.g., Brunnermeier and Pedersen, 2009).

Next we look at the cross-section of the FI sorted portfolios after accounting for ag-

gregate macroeconomic uncertainty factor of Bali et al. (2014). The annualized spread in returns and alphas decreases to 2.88% and 3.48%, respectively, but remains statistically significant (t-stats = 2.05 and 1.74). Notably, the uncertainty factor includes the default spread volatility and the term spread in its construction, both of which are likely correlated with financial intermediary health.

Controlling for the correlation factor of Buraschi et al. (2013), the annualized spread in returns and alphas remains high (6.24% and 8.88%, respectively) and significant (t-stats = 3.16 and 3.04), indicating little connection between the two factors.

We also examine the noise factor of Hu et al. (2013) and the option-based intermediary constraint factor of Chen et al. (2019), both of which could be theoretically related to our measure of financial intermediary health. In both cases, we observe little impact on the spread of either average returns or alphas when controlling for these two factors. In the case of Hu et al. (2013), the annualized spread in returns and alphas is 4.92% and 7.32%, respectively (t-stats = 3.04 and 2.56). And in the case of the Chen et al. (2019) factor, the annualized spread in returns and alphas is 5.40% and 6.60%, respectively (t-stats = 2.45 and 2.75). The results indicate that the HKM factor and the spread in hedge fund returns it generates are distinct from those produced by these two factors.

Lastly, we analyze the cross-section of the FI-sorted portfolios after accounting for the tail risk factor of Agarwal et al. (2017). The annualized spread in returns and alphas remains unaffected, at 5.76% and 7.32%, respectively. Both spreads continue to be statistically significant (t-stats = 2.57 and 3.14). We verify these results using an alternative tail risk measure, the jump risk measure of Cremers et al. (2015), and find very similar outcomes. Given the documented strong impact of tail risk on hedge fund returns (Agarwal et al., 2017), the intuitive link between financial intermediary risk and tail risk – since key tail events in our sample often coincided with adverse shocks to the financial sector – and the fact that both tail risk measures end in 2013, we conduct further investigation.

We supplement our analysis with another tail risk measure, BOE VIX Tail Hedge Index (VXTH), available up to July 2019. Controlling for the VXTH, we observe a reduction in the annualized spread in returns and alphas to 4.20% and 4.58%, respectively (t-stats = 2.34 and 2.30), suggesting a potential connection between tail risk and financial intermediary risk. However, the results also indicate that tail risk exposure does not fully account for the explanatory power of financial intermediary risk exposure.

In summary, across all alternative factors considered, the abnormal return spread between high and low FI-beta funds remains positive and statistically significant. Our results show that FI exposure has incremental power in explaining the cross-section of hedge fund returns. However, we wish to emphasize that our goal is not to claim the superiority of the HKM factor over all other existing factors. Rather, our aim is to show that a reasonable proxy for systematic financial intermediary risk – a factor firmly grounded in theory – plays a significant role in the cross-section of hedge fund returns.

5 Conclusion

Our study offers a comprehensive evaluation of systematic financial intermediary risk in the context of the cross-section of hedge fund returns, providing an important validation of this risk factor, which has been shown to be priced across multiple asset classes. We demonstrate that it is also priced in the cross-section of hedge funds, a segment notoriously difficult to reconcile with risk factors derived from other asset classes. Specifically, hedge funds with high exposure to financial intermediary risk outperform, on average, a low-exposure portfolio by approximately 7% per year on a risk-adjusted basis. This positive relation is not explained by fund characteristics or other known risk factors. Our results are particularly relevant for hedge fund investors, who should be aware that, although this exposure appears to be well-compensated by excess returns, many hedge funds significantly expose their investors to systematic financial intermediary risk.

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Table 1: Hedge fund summary statistics

The table presents summary statistics for hedge funds from the union database (BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS), segmented by different time periods and styles. N_{Funds} represents the total number of unique hedge funds. μ_{TS} and σ_{TS} are cross-sectional averages of each fund's average monthly excess returns and each fund's standard deviation of its monthly excess returns. σ_{XS} is the time-series average of monthly cross-sectional standard deviation of excess returns. μ_{TS}, σ_{TS}, and σ_{XS} are expressed in % and are annualized. The AUM statistics are time-series averages of monthly cross-sectional statistics (USD million), reflecting a typical distribution of hedge fund sizes in a specific month within the sample. The sample period runs from January 2000 to June 2021.

	N_{Funds}	μ_{TS}	σ_{TS}	σ_{XS}	AUM_{Mean}	AUM_{Q25}	AUM_{Q50}	AUM_{Q75}
Full sample	16,160	5.06	15.04	10.91	348	12	47	181
Sub-sample								
2000/01 – 2007/12	6,052	9.02	12.72	12.09	177	11	37	132
2008/01 – 2009/12	4,650	2.43	21.22	14.03	248	12	43	156
2010/01 – 2017/06	9,616	3.73	13.52	9.18	397	12	45	178
2017/07 – 2021/06	6,288	5.99	16.01	12.42	647	17	69	299
Style								
CTA	1,093	4.77	15.71	11.40	454	5	20	92
Emerging Markets	567	6.51	18.47	10.42	230	15	51	157
Event Driven	1,031	6.14	11.99	9.30	374	27	87	285
Global Macro	1,943	4.18	14.27	12.10	370	10	40	177
Long Only	992	7.41	18.91	8.84	329	15	54	176
Long Short	5,931	5.15	15.69	9.67	241	13	43	153
Market Neutral	278	2.71	11.04	6.47	172	15	51	165
Multi Strategy	1,228	2.98	14.60	10.35	468	12	41	174
Other	818	6.89	21.53	21.42	131	10	31	100
Relative Value	2,113	4.14	10.33	8.58	602	25	92	373
Sector	144	12.02	18.45	8.37	687	35	90	305
Short Bias	22	-1.86	16.70	8.81	36	13	23	40

Table 2: Risk-adjusted returns for financial intermediary beta-sorted portfolios

The table presents hedge fund portfolios' mean excess returns, alphas and betas. These equal-weight portfolios are formed by sorting on betas from 24-month rolling regressions of hedge fund excess returns on the financial intermediary factor of He et al. (2017), FI, controlling for the market excess return and rebalanced monthly. Hedge funds in Portfolio 1 have the lowest beta on the FI factor and funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return, and α_{CAPM} and α_{FH7} refer to CAPM and Fung and Hsieh (2004) seven-factor alpha, respectively. $\bar{r}$, α_{CAPM} and α_{FH7} are expressed in % per month. The post-formation betas are the betas from time-series regression of the 10 portfolios' excess returns on the FI and market factors. The pre-formation betas are the monthly means of hedge funds' rolling factor betas in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2021.

				Post betas		Pre betas	
	$\bar{r}$	α_{CAPM}	α_{FH7}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.26	−0.09	−0.39	−0.04	0.66	−0.46	1.00
	(0.30)	(0.20)	(0.21)	(0.07)	(0.12)	(0.03)	(0.07)
2	0.35	0.08	−0.16	0.02	0.42	−0.19	0.61
	(0.20)	(0.12)	(0.12)	(0.04)	(0.07)	(0.02)	(0.04)
3	0.34	0.11	−0.09	0.04	0.34	−0.10	0.47
	(0.18)	(0.11)	(0.10)	(0.03)	(0.05)	(0.01)	(0.03)
4	0.35	0.14	−0.04	0.03	0.31	−0.05	0.37
	(0.15)	(0.08)	(0.08)	(0.03)	(0.05)	(0.01)	(0.02)
5	0.39	0.20	0.03	0.04	0.28	−0.00	0.31
	(0.14)	(0.09)	(0.07)	(0.03)	(0.05)	(0.01)	(0.02)
6	0.42	0.23	0.09	0.06	0.25	0.04	0.29
	(0.14)	(0.09)	(0.08)	(0.02)	(0.04)	(0.01)	(0.02)
7	0.41	0.21	0.05	0.07	0.25	0.08	0.27
	(0.14)	(0.10)	(0.10)	(0.03)	(0.05)	(0.02)	(0.02)
8	0.44	0.22	0.05	0.09	0.27	0.13	0.27
	(0.16)	(0.13)	(0.13)	(0.04)	(0.06)	(0.02)	(0.03)
9	0.51	0.25	0.10	0.13	0.28	0.22	0.24
	(0.18)	(0.15)	(0.14)	(0.04)	(0.07)	(0.03)	(0.03)
10 (high)	0.75	0.44	0.19	0.23	0.24	0.52	0.12
	(0.24)	(0.20)	(0.17)	(0.05)	(0.08)	(0.05)	(0.10)
10–1	0.48	0.53	0.58	0.27	−0.41	0.98	−0.88
	[2.26]	[2.13]	[2.23]	[4.22]	[−3.76]	[14.74]	[−7.92]

Table 3: Hedge fund financial intermediary risk premium

The table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly hedge fund excess returns on rolling financial intermediary betas. Betas are estimated by 24-month rolling regressions of hedge fund excess returns on the financial intermediary factor, FI, and the market excess return. Time $t+1$ monthly hedge fund excess returns (in %) are regressed on the time t rolling FI and market betas as well as fund's previous month's return (r_t, in %), age (in months), log of AUM, management fee (in %), incentive fee (in %), a high watermark indicator for the fund, a lockup provision indicator for the fund, the redemption notice (in days), and the minimum fund investment amount (USD million). Style fixed effects are dummies following the Kosowski et al. (2016) mapping. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). The total number of observations, the number of time-series (TS) observations, the mean number of cross-sectional (XS) observations as well as the mean R^2 of the cross-sectional regressions are also reported. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample runs from January 2000 to June 2021.

	I	II	III	IV
β^{FI}	0.303**	0.272**	0.693***	0.477**
	(0.126)	(0.117)	(0.244)	(0.219)
β^{M}			0.355*	0.314*
			(0.193)	(0.169)
r_t				0.059***
				(0.010)
Age				−0.006***
				(0.002)
log(AUM)				−0.009
				(0.013)
Managment fee				0.047***
				(0.014)
Incentive fee				0.004**
				(0.002)
High water mark				0.065**
				(0.027)
Lockup				0.060**
				(0.024)
Redemption notice				0.001***
				(0.000)
Minimum investment				0.001
				(0.000)
Constant	0.422***			
	(0.125)			
Style fixed effects	No	Yes	Yes	Yes
Total observations	1,167,620	1,167,620	1,167,620	999,564
TS observations	258	258	258	258
Mean XS observations	4,526	4,526	4,526	3,874
Mean R^2	0.014	0.051	0.094	0.112

Table 4: Long-short portfolio returns by sub-sample and hedge fund style

The table presents mean excess returns and hedge fund portfolios' alphas and betas for the high minus low portfolio. A detailed table description can be found in Table 2. The last column reports the time-series mean of the total number of funds in each cross-section. Full sample refers to the sample comprising all the hedge fund databases (Barclayhedge, Eurekahedge, HFR, Morningstar and TASS) from 2000/01 to 2021/06 as in Table 2. The original sample period refers to the sample period from the previous version of the paper that ran until 2017/06. The original sample considers only the funds from Eurekahedge. Subsamples denoted as > USD 20M, > USD 50M, and > USD 100M represent cases where hedge fund AUM must exceed the specified cutoff for inclusion in the test portfolios. The Styles panel reports the results for the analysis conducted on samples comprised of funds belonging to the respective Kosowski et al. (2016) style. Only the styles where we can allocate at least five funds to both the long and short legs of the portfolio, respectively, each month, are considered. The Traded factor panel presents the results where the FI factor is replaced by the traded version, constructed as the value-weighted return of a portfolio of Primary Dealers.

				Post betas		Pre betas		Mean num.
	$\bar{r}$	α_{CAPM}	α_{FH7}	β^{FI}	β^{M}	β^{FI}	β^{M}	of funds
Samples								
Full sample	0.48	0.53	0.58	0.27	−0.41	0.98	−0.88	5,416
	[2.26]	[2.13]	[2.23]	[4.22]	[−3.76]	[14.74]	[−7.92]	
Original sample period	0.62	0.68	0.70	0.21	−0.43	0.91	−0.78	4,272
	[2.92]	[3.07]	[3.01]	[3.79]	[−4.27]	[19.00]	[−8.25]	
Original sample	0.65	0.62	0.58	0.18	−0.17	0.98	−0.79	1,272
	[3.16]	[2.41]	[1.90]	[2.85]	[−1.78]	[17.01]	[−8.35]	
> USD 20M	0.45	0.49	0.65	0.24	−0.36	0.87	−0.80	3,937
	[2.30]	[2.13]	[2.39]	[3.28]	[−3.02]	[15.83]	[−7.82]	
> USD 50M	0.43	0.45	0.64	0.24	−0.33	0.82	−0.74	2,916
	[2.25]	[1.98]	[2.28]	[3.01]	[−2.77]	[15.87]	[−7.81]	
> USD 100M	0.42	0.42	0.66	0.22	−0.27	0.79	−0.68	2,170
	[2.29]	[1.89]	[2.27]	[2.71]	[−2.40]	[15.63]	[−7.69]	
Styles								
CTA	0.13	0.12	0.43	0.01	0.01	0.99	−0.89	302
	[0.62]	[0.52]	[1.39]	[0.10]	[0.10]	[24.88]	[−8.35]	
Emerging Markets	0.52	0.52	0.36	0.11	−0.13	1.09	−1.05	155
	[1.52]	[1.39]	[0.83]	[1.10]	[−1.05]	[14.62]	[−10.28]	
Event Driven	0.44	0.46	0.57	0.11	−0.16	0.66	−0.61	310
	[2.38]	[2.36]	[2.11]	[2.62]	[−1.92]	[21.62]	[−14.73]	
Global Macro	0.05	−0.00	0.12	0.15	−0.10	0.90	−0.74	481
	[0.27]	[−0.01]	[0.56]	[2.56]	[−0.87]	[16.34]	[−7.33]	
Long Short	0.50	0.57	0.61	0.33	−0.52	0.98	−0.88	1,668
	[2.14]	[2.13]	[1.89]	[3.91]	[−3.43]	[13.27]	[−8.65]	
Relative Value	0.37	0.35	0.58	0.10	−0.08	0.63	−0.50	567
	[2.43]	[1.64]	[2.08]	[2.73]	[−0.87]	[19.13]	[−7.69]	
Traded factor								
Traded FI factor	0.55	0.59	0.44	0.31	−0.45	1.22	−1.26	5,416
	[2.49]	[2.23]	[1.52]	[4.08]	[−3.91]	[17.86]	[−10.54]	

Table 5: Double Sorts

This table presents results for portfolios sorted of the betas on the financial intermediary factor, FI, controlling separately for exposure to the liquidity factor of Pástor and Stambaugh (2003), the macroeconomic uncertainty factor of Bali et al. (2014), the correlation factor of Buraschi et al. (2013), the noise factor of Hu et al. (2013), the option-based constraint measure (CJN) of Chen et al. (2019), the tail risk factor of Agarwal et al. (2017), the jump risk factor of Cremers et al. (2015), the CBOE VIX Tail Hedge Index (VXTH), an option-based measure of tail risk. Quintiles based on the controlling factor exposure are determined monthly, based on regressions of excess returns on the respective measure as well as the market excess return, on rolling 24-month windows. Each of these portfolios are then subdivided into five quintiles based on their past FI beta (formed monthly and equal weighted). We obtain five FI portfolios controlling for the given factor by averaging each FI quintile over the five control portfolios, as in Ang et al. (2006). The table reports mean excess returns (in % per month) and Fung and Hsieh (2004) seven-factor alphas (in % per month). Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in parentheses. The sample period is indicated for each measure separately.

	Liquidity		Uncertainty		Correlation		Noise		CJN		Tail		Jump		VXTH	
	2000/01–2021/06		2000/01–2021/06		2000/01–2012/07		2000/01–2021/06		2000/01–2013/01		2000/01–2013/01		2000/01–2012/04		2008/04–2019/07	
	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}
1 (low)	0.33	−0.20	0.35	−0.21	0.23	−0.31	0.25	−0.31	0.29	−0.17	0.27	−0.19	0.30	−0.26	0.06	−0.42
	(0.21)	(0.13)	(0.22)	(0.15)	(0.34)	(0.23)	(0.22)	(0.14)	(0.34)	(0.23)	(0.35)	(0.22)	(0.33)	(0.25)	(0.31)	(0.15)
2	0.35	−0.05	0.36	−0.04	0.33	−0.01	0.34	−0.07	0.36	0.00	0.36	−0.01	0.32	−0.02	0.19	−0.21
	(0.16)	(0.08)	(0.17)	(0.09)	(0.23)	(0.14)	(0.16)	(0.08)	(0.23)	(0.14)	(0.23)	(0.13)	(0.24)	(0.16)	(0.26)	(0.10)
3	0.39	0.01	0.40	0.05	0.38	0.11	0.41	0.02	0.43	0.14	0.42	0.11	0.38	0.13	0.23	−0.14
	(0.15)	(0.08)	(0.15)	(0.08)	(0.21)	(0.11)	(0.15)	(0.08)	(0.20)	(0.12)	(0.20)	(0.13)	(0.21)	(0.11)	(0.24)	(0.10)
4	0.42	0.04	0.40	0.04	0.44	0.22	0.45	0.09	0.50	0.22	0.53	0.25	0.48	0.24	0.30	−0.08
	(0.16)	(0.10)	(0.15)	(0.10)	(0.22)	(0.13)	(0.15)	(0.10)	(0.19)	(0.12)	(0.20)	(0.12)	(0.22)	(0.12)	(0.24)	(0.12)
5 (high)	0.61	0.12	0.59	0.08	0.76	0.43	0.65	0.18	0.74	0.38	0.74	0.42	0.81	0.53	0.41	−0.03
	(0.21)	(0.14)	(0.20)	(0.13)	(0.28)	(0.19)	(0.20)	(0.14)	(0.27)	(0.17)	(0.26)	(0.17)	(0.30)	(0.18)	(0.32)	(0.15)
5—1	0.28	0.32	0.24	0.29	0.52	0.74	0.41	0.49	0.45	0.55	0.48	0.61	0.51	0.79	0.35	0.39
	[2.21]	[2.19]	[2.05]	[1.74]	[3.16]	[3.04]	[3.04]	[2.56]	[2.45]	[2.75]	[2.57]	[3.14]	[2.92]	[3.21]	[2.34]	[2.20]

Figure 1: Cumulative Portfolio Returns

This figure shows the cumulative return of investing one dollar into several portfolios. Panels (a) and (b) display the performance of a portfolio that is long in funds from the highest decile of FI betas and short in funds from the lowest FI beta decile, alongside the Credit Suisse Hedge Fund Index (red). Panels (c) and (d) present the cumulative returns of the portfolios with the lowest (P1, red) and highest (P10, blue) FI beta, as well as an equal-weighted combination of the two middle portfolios (P5 and P6, green). Panels (a) and (c) focus on the cumulative returns of these investments, while Panels (b) and (d) illustrate the abnormal performance – specifically, the cumulative returns of a strategy where exposures to the seven Fung and Hsieh (2004) factors are hedged out using full-sample beta estimates. The sample period runs from January 2000 to June 2021.

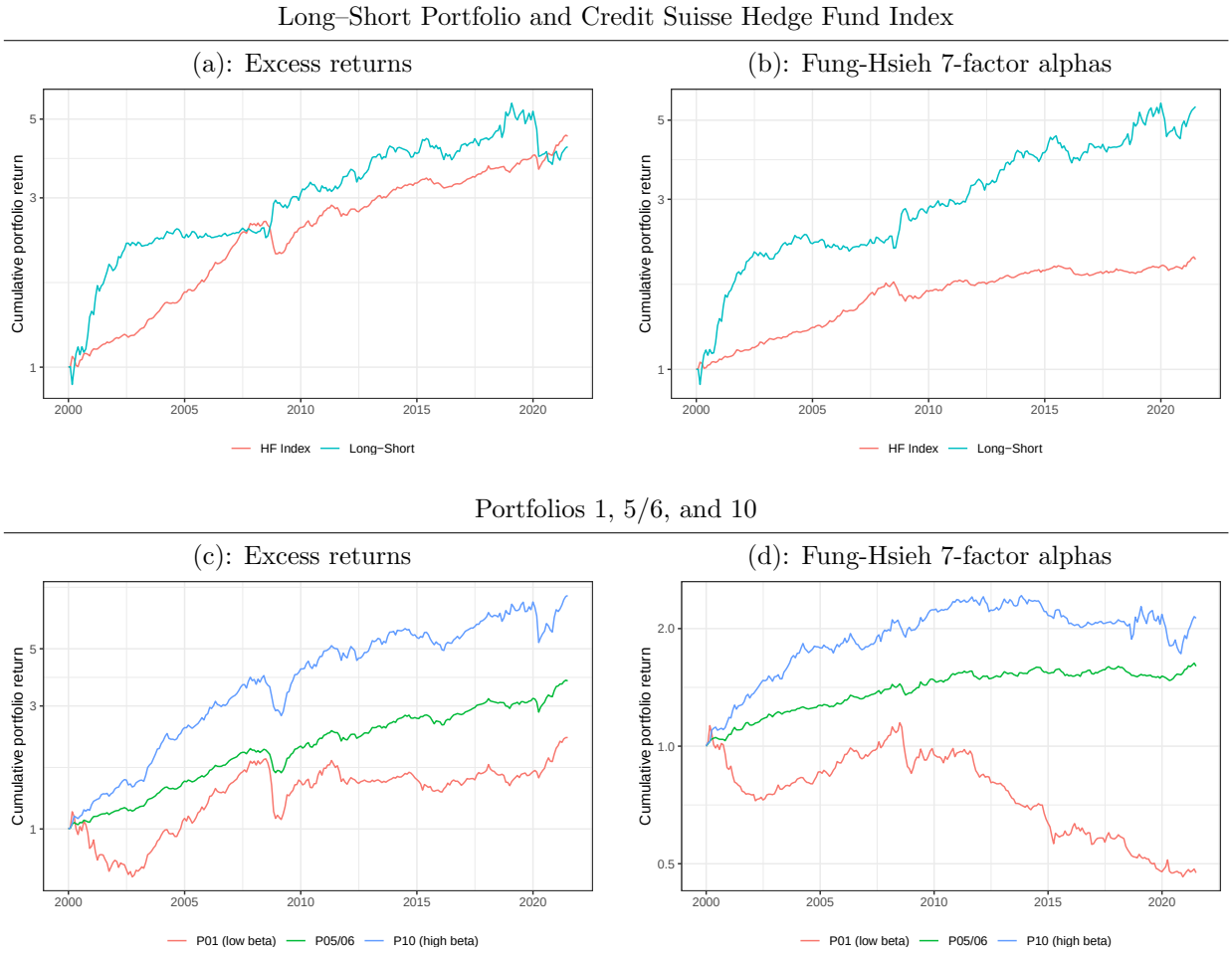


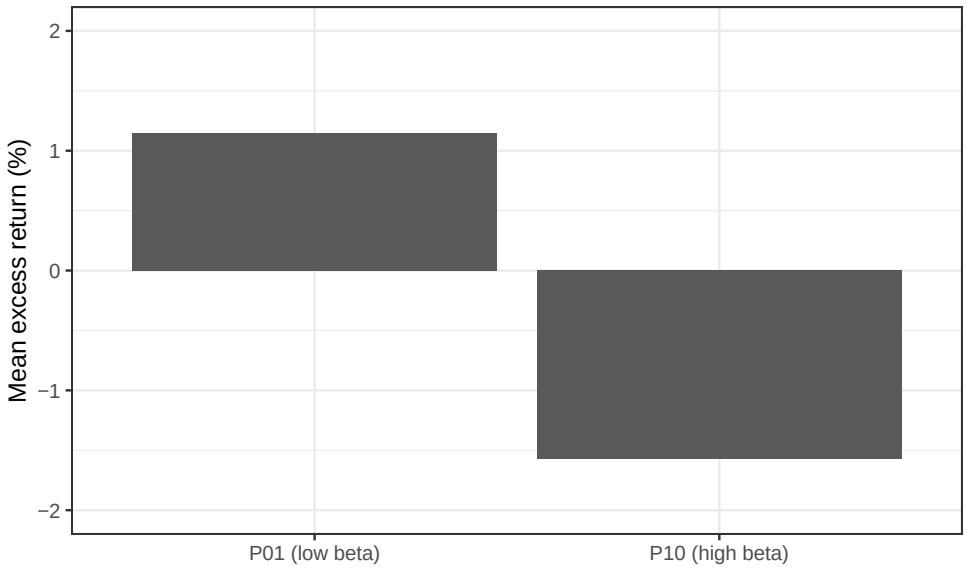
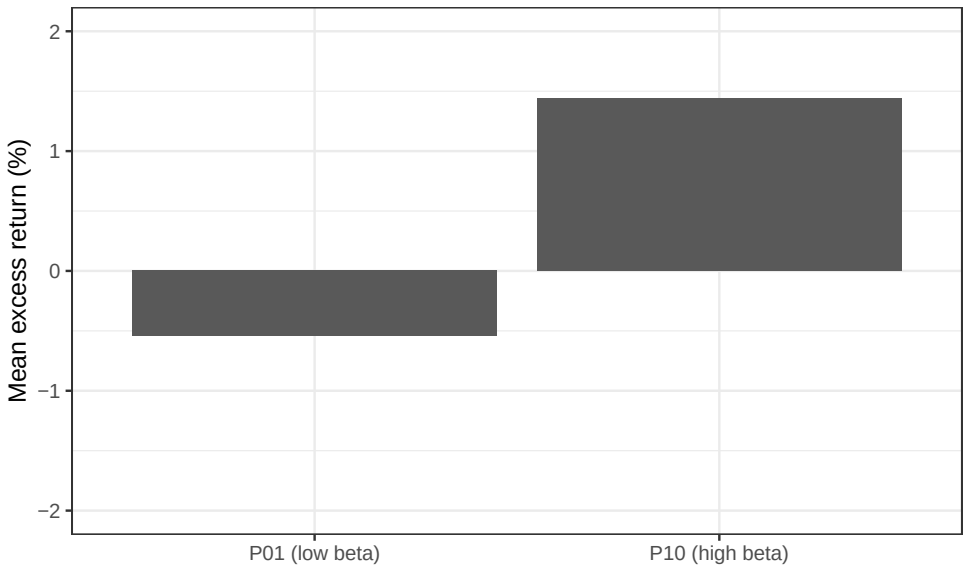
Figure 2: Cumulative return premiums

This figure shows the cumulative values of FI premiums estimated from the cross-sectional Fama-MacBeth regressions of monthly hedge fund excess returns on FI betas and controls as in Table 3. The sample period runs from January 2000 to June 2021.

Figure 3: FI-sorted hedge fund portfolio performance during extreme FI realizations

This figure shows the average excess returns (monthly, in %) for two FI beta sorted portfolios (deciles one and ten, orthogonalized with respect to the market return) in the twenty months with the lowest (panel a) and highest (panel b) FI factor realizations (orthogonalized with respect to the market return), respectively. The decile portfolios are constructed by monthly portfolio sorts on the loading on the FI factor (controlling for the market return), as in Table 2. The sample period runs from January 2000 to June 2021.

(a) 20 lowest FI factor realization months



(b) 20 highest FI factor realization months