Internet Appendix

Hedge Funds and Prime Broker Risk *

January 17, 2024

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IA-.A Creating a union database of hedge fund managers

Step 0: Basic filters

Separately, for each of the five hedge fund databases (BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS), we apply the following basic filters:

- Retain only the hedge funds that report net-of-fees returns.
- Exclude any funds-of-funds.
- Exclude funds that never report their currency, style, or AUM.
- Exclude any hedge funds that report consecutive identical returns for more than three months (e.g., June 2002: 2%, July 2002: 2%, August 2002: 2%) if such returns represent more than 5% of the total returns reported by that fund. See Almeida, Ardison, and Garcia (2020) for details.
- Exclude any hedge funds that report more than twice "blocks" of identical returns. Specifically, we consider blocks of two to twelve returns. For example, repeated blocks of two returns could look like this: June 2002: 2%, July 2002: 2.5%, August 2002: 2%, August 2002: 2.5%. See Almeida et al. (2020) for details.
- When a hedge fund has multiple share classes, we consider only a single share class for each fund (retaining the fund with the longest time series) and aggregate their AUMs.

Step 1: Name cleaning

We first standardize and clean manager names by applying the following procedure to the list of manager names of all hedge fund databases as well as the Thomson Reuters 13F database:

- Remove any non-UTF-8 character
- Make everything uppercase
- Remove unnecessary whitespaces
- Remove terms in parentheses (often the location, e.g., 'Cayman')
- Remove punctuation (e.g. ',' in front of LLC)
- Standardize use of & / 'and'
- Standardize acronyms to be spelled without whitespaces in between (e.g. 'AQR' instead of 'A Q R')
- Replace standard abbreviations (e.g. 'MGMT' with 'MANAGEMENT')
- Remove legal form (such as 'LLC')

- Remove region from the end of the name (such as 'Luxemburg')

Step 2: Identify duplicate managers within a database

Next, based on the standardized names, we identify all managers with the same standardized name. If the database uses manager IDs (Lipper/TASS and BarclayHedge), we replace the IDs of duplicates with the first ID within each group of duplicates. For the other databases (CISD, Eurekahedge, HFR), we assign numeric IDs based on the standardized name; that is, managers sharing the same standardized name receive the same ID. In the 13F database, different IDs (mgrno), even with identical standardized names, typically represent different filers. Hence, we keep them separate and will use additional characteristics to attempt merging with the other databases later.

Step 3: Initial name merge based on standardized names

We begin by merging manager names from BarclayHedge and Lipper/TASS. Subsequently, we merge these with the union of CISD, HFR, and Eurekahedge, in this order. For each name in database A, we loop through all names in database B, comparing them using the following procedure:

We rank matches in the following order (best to worst):

- The standardized names of A and B are exactly equal
- The standardized names of A and B contain multiple unique words (words that are not on the list of abbreviations, e.g. 'MANAGEMENT') and those are exactly equal. If there are multiple such cases, prefer the one where the Levenshtein distance between the two is smallest.
- The standardized names of A and B contain one unique word, that is exactly equal, and there is only one non-unique word missing in either A or B (e.g. 'XYZ CAPITAL MANAGEMENT' and 'XYZ CAPITAL') preventing a perfect match.
- The standardized names of A and B contain one unique word, that is exactly equal, and only one of the non-unique words from A and B is different (e.g. 'XYZ CAPITAL MANAGEMENT' and 'XYZ CAPITAL ADVISORS'). If there are multiple such cases, prefer the one where the Levenshtein distance between the two is smallest.
- The standardized names of A and B contain one unique word, that is exactly equal, and multiple of the non-unique words from A and B are different. If there are multiple such cases, prefer the one where the Levenshtein distance between the two is smallest.

We retain all perfect matches (as per the first bullet point) and other matches that are the best match for both A (from all possible matches in B) and vice versa. An example where this condition is not met: XYZ Capital' from B could be the best match for XYZ CAPITAL MANAGEMENT' in A. However, if A also contains an XYZ Capital', this would be the best match for XYZ Capital' from B. Consequently, XYZ CAPITAL MANAGEMENT' from A would not have a match in B. We assume that database A intentionally listed XYZ CAPITAL MANAGEMENT' and 'XYZ Capital' as separate managers.

Step 4: Identify duplicate funds using return correlations

We first merge fund returns from BarclayHedge and CISD, then generate the full correlation matrix for all funds. Any funds with a correlation of $\geq$ 99% (based on either reported returns or returns converted to USD), and sharing an overlapping period of at least 12 months, are flagged as duplicates.

From these groups of potential duplicates, we retain the one with the longest history of returns and record the IDs of other members in the group. Next, using the resultant union database, we merge it with Eurekahedge, HFR, and Lipper/TASS, following the same procedure, in that order. Ultimately, this results in a consolidated database of fund IDs, each representing the same fund. This includes different share classes of the same fund within one database, as well as identical funds listed across multiple databases.

Step 5: Manually overwrite manager names, using information from the correlation exercise

From the correlation analysis, we compile a list of managers with funds showing 99% correlation but recorded as different entities. We manually review this list to determine if any of these managers are, in fact, the same. For instance, discrepancies may arise when one database uses an older name for a manager, while another uses a more recent name following any name changes. This process also helps us identify several typos that hindered matching in the initial iteration

Step 6: Repeat name matching procedure, using correlation as tie-breaker

We repeat the matching procedure from step 3, but include the manual fixes from step 5. Also, we additionally use the maximum correlation between any two funds of two managers as an additional tie-breaker, in case of multiple valid name matches.

Step 7: Match names with 13F

Lastly, we apply the same name matching techniques to align the union database of hedge fund managers with the 13F database. For all matches meeting any of the criteria outlined in step 3, we use several tie-breakers: the median absolute value of the logarithm of the ratio of holdings market value to reported fund AUM (rounded to whole numbers) serves as the primary tie-breaker. The secondary tie-breaker is the number of overlapping monthly observations between manager returns and 13F database returns, rounded to the nearest hundred. Finally, the quality of the name match, as measured by the Levenshtein distance, is used as the last tie-breaker.

Main sample of hedge fund managers

To be included in our main sample of hedge fund managers, a number of criteria must be met:

- Manager with $\leq$5 funds
- each of these up to 5 funds are 'eligible' (equity-related style, some North America exposure — specifics below)

- Hedge fund (not fund of fund, CTA or MAF)
  - Kosowski Style $\in$ (Sector, Long/Short, Long Only, Market-Neutral, Multi-Strategy, Event Driven)
  - Main style cannot contain ("debt", "bond", "etfs", "europe", "EUR", "real estate")
  - Sub-style cannot contain ("fixed", "multi", "currency", "debt", "bond", "credit", "emerging", "commodities", "option", "volatility", "mortgage", "etfs", "macro", "insurance")
  - If we have non-missing exposure to North America, it cannot be 0
  - If we have non-missing geographical focus, it must be $\in$ (N. America, North America, Global)
  - If we have non-missing focus-us and focus north-america, one of them has to be =1
  - If we have one of focus-us and focus north-america non-missing, it has to be =1
  - If we have non-missing focus-other, it must be =0, unless we also have neither focus-us=1 or focus north-america=1
  - If we have non-missing ae-equities, it cannot be =0

- 13F must classify the manager as typecode (3=investment companies and their managers, 4=independent investment advisor, 5=all others) at least once (so they cannot only be classified as (1=bank, 2=insurance company))

- At least 24 monthly observations

- Median (over life of manager) of $|log(TNAratio)| < log(5)$
  - TNA-Ratio = $\frac{aum13f}{aumMgr}$
  - We measure the TNA ratio once with aumMgr and once with aumMgrMax (which is the maximum AUM you get, when you always use the largest aums for a particular fund, when there are alternative numbers from different databases)
  - only one of these TNA ratios (either the aumMgr-based or the aumMgrMax-based) has to satisfy the constraint

Full sample of 13F filers

As a robustness check, we work with a larger sample that, in addition to the managers selected above, includes managers with less strict criteria:

- Manager with >5 but ≤10 funds or manager with ≤5 funds, some or all of which are not 'eligible' (as defined above)

- 13F must classify the manager as typecode (3=investment companies and their managers, 4=independent investment advisor, 5=all others) at least once (so they cannot only be classified as (1=bank, 2=insurance company))
- At least 24 monthly observations
- No other restrictions (in particular, no TNA-ratio criterion and no ‘eligibility’ check)

IA-.B The effect of correlation between observed and unobserved positions

In the paper, we assume the correlation between $\widehat{\beta}_i^{\mathrm{U}}$ and $\widehat{\beta}_i^{\mathrm{O}}$ to be zero. Below, we explore the effects of assuming a non-zero correlation/covariance.

$$\widehat{b} = \bar{\ell}(1-\bar{\omega}) - \bar{\ell}\ell_i^S \bar{s}(1-\bar{\omega}) + \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)}. \tag{IA-2}$$

$$\begin{aligned}
\widehat{a} &= \bar{\beta} - \widehat{b} \times \bar{\beta}^O \\
&= \bar{\ell}(1-\bar{\omega})\bar{\beta}^{\mathrm{O}} + \bar{\ell}\bar{\omega}\bar{\beta}^{\mathrm{U}} \\
&- \bar{\ell}\bar{\ell}^S\bar{\beta}^{\mathrm{S}} + \bar{\beta}^{\mathrm{PBCh.}} - \left[\bar{\ell}(1-\bar{\omega}) - \bar{\ell}\ell_i^S\bar{s}(1-\bar{\omega}) + \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)}\right] \times \bar{\beta}^O \\
&= \bar{\ell}\bar{\omega}\bar{\beta}^{\mathrm{U}} - \bar{\ell}\bar{\ell}^S\bar{s}((1-\bar{\omega})\bar{\beta}^{\mathrm{O}} + \bar{\omega}\bar{\beta}^{\mathrm{U}}) + \bar{\beta}^{\mathrm{PBCh.}} + \bar{\ell}\bar{\ell}^S\bar{s}(1-\bar{\omega})\bar{\beta}^O - \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)} \times \bar{\beta}^O \\
&= \left(1-\bar{\ell}^S\bar{s}\right)\bar{\ell}\bar{\omega}\bar{\beta}^U + \bar{\beta}^{\mathrm{PBCh.}} - \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)} \times \bar{\beta}^O.
\end{aligned} \tag{IA-3}$$

As evident from the final equation, a positive correlation between $\widehat{\beta}_i^{\mathrm{U}}$ and $\widehat{\beta}_i^{\mathrm{O}}$ will reduce the model-implied estimate of a. This, in turn, lowers the threshold for $\widehat{\beta}^{\mathrm{PBCh.}}$ to exceed 0. Conversely, a negative correlation would have the opposite effect. However, justifying such a negative correlation between FI-betas of observed and unobserved positions ex-ante is challenging.

Table IA.1: Event study matched sample

This table presents panel regressions of monthly hedge fund risk-adjusted returns (expressed in %) on various indicator variables and their interactions. For details see caption to Table 2 in the paper. The sample comprises only the hedge funds that were clients of the affected prime brokers two months prior to the respective prime broker event and a matched group of hedge funds not affiliated with these prime brokers. Hedge funds are matched based on the number of prime brokers, style, AUM, and past returns. The sample period runs from January 2000 to June 2021.

	I	II	III	IV	V	VI
Lehman Event	−1.588	−1.588	−1.501	−1.455	−0.783	−0.822
	(1.085)	(1.085)	(1.136)	(1.113)	(1.007)	(0.804)
Lehman Event × Lehman Client	−1.171	0.509	0.556*	0.511	−0.273	0.100
	(0.718)	(0.386)	(0.300)	(0.334)	(0.673)	(0.620)
Lehman Event × Lehman Unique Client		−3.066***	−2.902***	−2.845***	−2.674***	−2.139**
		(0.797)	(0.659)	(0.678)	(0.686)	(0.846)
Lehman Event × Single PB				−0.059	−0.086*	−0.024
				(0.091)	(0.046)	(0.076)
PB Events	−0.649	−0.650	−0.584	−0.542	−0.474	−0.435
	(0.571)	(0.571)	(0.552)	(0.419)	(0.332)	(0.282)
PB Events × PB Client	−0.288**	0.065	0.077	0.046	0.071	0.030
	(0.127)	(0.130)	(0.140)	(0.137)	(0.137)	(0.126)
PB Events × PB Unique Client		−0.534***	−0.454**	−0.408**	−0.298**	−0.283*
		(0.199)	(0.196)	(0.168)	(0.150)	(0.144)
PB Events × Single PB				−0.059	−0.091	−0.042
				(0.268)	(0.211)	(0.178)
Observations	152,676	152,676	151,569	151,569	151,569	151,569
Adjusted R^2	0.014	0.014	0.027	0.027	0.026	0.026
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Event window	1 & 1	1 & 1	1 & 1	1 & 1	1 & 2	1 & 3

Table IA.2: Risk-adjusted returns of FI beta-sorted portfolios (13F filers)

The table presents mean excess returns and hedge fund portfolios' alphas and betas. For details see caption to Table 4 in the paper.
The difference here is that the sample is comprised of only the hedge funds whose managers file form 13F, typically US equity funds.

				Post betas		Pre betas	
	$\bar{r}$	α_{CAPM}	α_{FH7}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.32	−0.11	−0.28	−0.13	0.87	−0.39	1.06
	(0.27)	(0.15)	(0.18)	(0.08)	(0.14)	(0.04)	(0.08)
2	0.36	0.02	−0.04	−0.04	0.61	−0.18	0.73
	(0.20)	(0.08)	(0.10)	(0.05)	(0.07)	(0.02)	(0.05)
3	0.35	0.08	−0.02	−0.01	0.45	−0.10	0.56
	(0.17)	(0.08)	(0.08)	(0.03)	(0.06)	(0.02)	(0.03)
4	0.35	0.08	−0.01	0.03	0.40	−0.05	0.46
	(0.16)	(0.08)	(0.07)	(0.03)	(0.05)	(0.01)	(0.02)
5	0.43	0.19	0.13	0.04	0.35	−0.01	0.39
	(0.15)	(0.10)	(0.07)	(0.02)	(0.04)	(0.01)	(0.02)
6	0.46	0.22	0.13	0.03	0.35	0.02	0.34
	(0.14)	(0.09)	(0.09)	(0.02)	(0.04)	(0.01)	(0.02)
7	0.44	0.20	0.15	0.07	0.31	0.06	0.34
	(0.15)	(0.11)	(0.10)	(0.03)	(0.05)	(0.01)	(0.02)
8	0.61	0.34	0.29	0.08	0.35	0.10	0.34
	(0.19)	(0.13)	(0.12)	(0.03)	(0.06)	(0.01)	(0.02)
9	0.66	0.34	0.33	0.12	0.37	0.18	0.34
	(0.21)	(0.13)	(0.11)	(0.03)	(0.06)	(0.02)	(0.03)
10 (high)	0.87	0.45	0.45	0.23	0.41	0.40	0.28
	(0.29)	(0.18)	(0.18)	(0.06)	(0.09)	(0.03)	(0.04)
10–1	0.55	0.56	0.73	0.36	−0.46	0.79	−0.78
	[2.54]	[2.32]	[2.39]	[3.92]	[−2.94]	[14.68]	[−6.55]

Table IA.3: Double Sorts

This table presents results for portfolios sorted on the loading 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, Brown, and Caglayan (2014), the correlation factor of Buraschi, Kosowski, and Trojani (2013), the tail risk factor of Agarwal, Ruenzi, and Weigert (2017), the noise factor of Hu, Pan, and Wang (2013) the jump risk factor of Cremers, Halling, and Weinbaum (2015), the option-based constraint measure (CJN) of Chen, Joslin, and Ni (2019), 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 loading (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, Hodrick, Xing, and Zhang (2006).
Reported are 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 brackets. The sample period is indicated for each measure separately.

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

Table IA.4: Risk-adjusted returns for financial intermediary beta-sorted portfolios

The table repeats the exercise described and shown in Table 4 of the paper, but focuses on the return spread between high and low FI-beta portfolios (10–1) for several Kosowski, Joenväärä, and Tolonen (2016) styles. We focus on styles with at least 5 funds in the long and short leg in each month. The last column reports the time-series average of the average number of funds in the long and short leg.

				Post betas		Pre betas		
	$\bar{r}$	α_{CAPM}	α_{FH7}	β^{FI}	β^{M}	β^{FI}	β^{M}	N funds
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]	

Table IA.5: Systematic prime-broker relationship channel (all 13F hedge fund matches)

This table presents the results from a test for excess financial intermediary risk exposure described in subsection 5.2 of the main paper. For details see caption to Table 7 in the paper.
The difference here is that we use a larger, less strictly selected sample of hedge fund managers, as described in Section IA-.A of the Internet Appendix.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta^{\text{X}}_{Hlds})}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta^{\text{X}}_{Ind})}$
Panel A: All hedgefunds who file 13F								
Hedge Funds								
β^{FI}	0.021	0.340	0.181	1,305	0.004	0.017	10.34%	10.80%
	(0.004)	(0.043)				[0.000]		
β^{FI}_{down}	0.081	0.384	0.140	923	0.022	0.059	26.42%	23.76%
	(0.009)	(0.045)				[0.000]		
β^{FI}_{up}	0.007	0.291	0.129	992	0.015	−0.008	-3.89%	−4.16%
	(0.006)	(0.048)				[0.913]		

Table IA.6: Systematic prime-broker relationship channel (alternative null factor models)

This table presents the results from a test for excess financial intermediary risk exposure described in subsection 5.2 of the main paper. For details see caption to Table 7 in the paper.
The difference here is that we use alternative factor models.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta^{\text{X}}_{Hlds})}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta^{\text{X}}_{Ind})}$
Panel A: Fama French Three Factors and FI								
Hedge Funds								
β^{FI}	0.030	0.498	0.263	523	0.006	0.024	17.07%	21.27%
	(0.005)	(0.054)				[0.000]		
β^{FI}_{down}	0.064	0.578	0.318	357	0.019	0.046	22.71%	30.12%
	(0.011)	(0.069)				[0.000]		
β^{FI}_{up}	0.004	0.524	0.264	382	0.010	−0.006	-3.31%	−3.39%
	(0.008)	(0.069)				[0.763]		
Mutual Funds								
β^{FI}	0.003	0.909	0.850	1,834	0.001	0.002	2.40%	1.62%
	(0.001)	(0.011)				[0.008]		
β^{FI}_{down}	0.010	0.930	0.841	1,251	0.007	0.003	2.57%	1.97%
	(0.002)	(0.017)				[0.085]		
β^{FI}_{up}	0.001	0.933	0.835	1,410	−0.001	0.002	1.88%	0.96%
	(0.001)	(0.016)				[0.082]		
Panel B: Fama French Five Factors and FI								
Hedge Funds								
β^{FI}	0.033	0.441	0.206	523	0.002	0.032	22.12%	27.93%
	(0.005)	(0.063)				[0.000]		
β^{FI}_{down}	0.069	0.462	0.193	357	0.014	0.055	26.32%	37.02%
	(0.013)	(0.103)				[0.000]		
β^{FI}_{up}	0.014	0.514	0.262	382	0.006	0.008	4.13%	3.95%
	(0.009)	(0.072)				[0.186]		
Mutual Funds								
β^{FI}	0.001	0.896	0.828	1,834	−0.000	0.001	1.53%	0.93%
	(0.001)	(0.011)				[0.083]		
β^{FI}_{down}	0.010	0.907	0.718	1,251	0.005	0.005	4.34%	3.16%
	(0.003)	(0.024)				[0.056]		
β^{FI}_{up}	−0.000	0.927	0.831	1,410	−0.001	0.001	0.91%	0.42%
	(0.001)	(0.016)				[0.257]		

Figure IA.1: Event study of prime broker shocks

The figure shows, in event time, cumulative equal-weighted hedge fund risk-adjusted return indexes. These indexes comprise returns from clients of the affected prime brokers (solid lines) and those from a matched group of hedge funds not affiliated with these brokers (dashed lines). The three events considered are the failure of Bear Stearns (March 2008), the trading loss scandal of UBS (September 2011), and the trading loss scandal of JP Morgan (April 2012). The shaded region delineates a three-month event window. The indexes are set to 100 two months prior to each event month. The risk-adjusted returns are equal to the constant plus residuals from individual regressions of hedge fund excess returns on the Fung and Hsieh (2004) seven factors. Hedge funds are matched based on the number of prime brokers, style, AUM, and past returns. The figure differentiates between hedge funds with multiple prime brokers (blue shades) and those with only one prime broker (red shades).

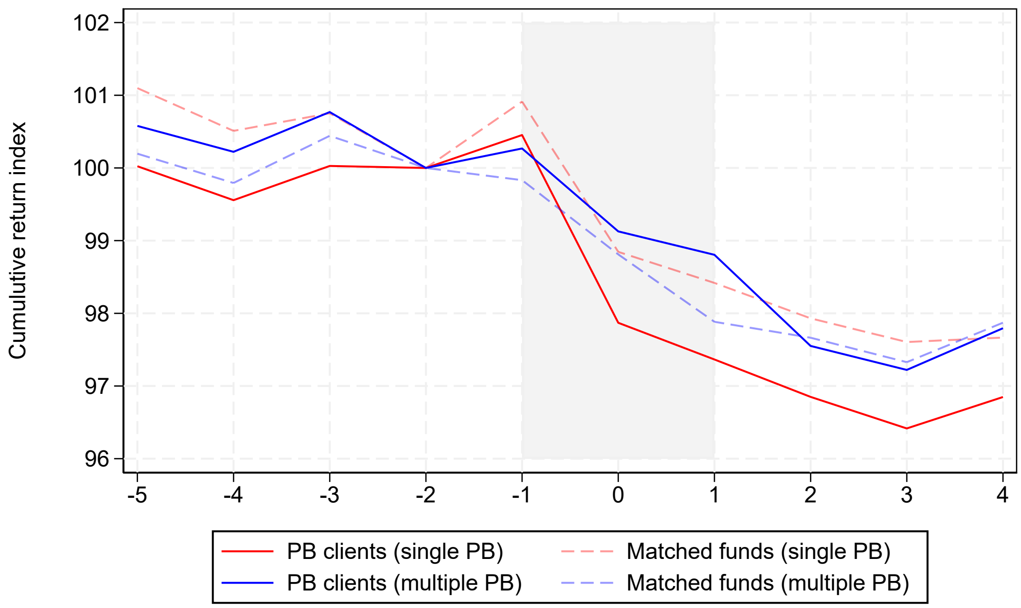
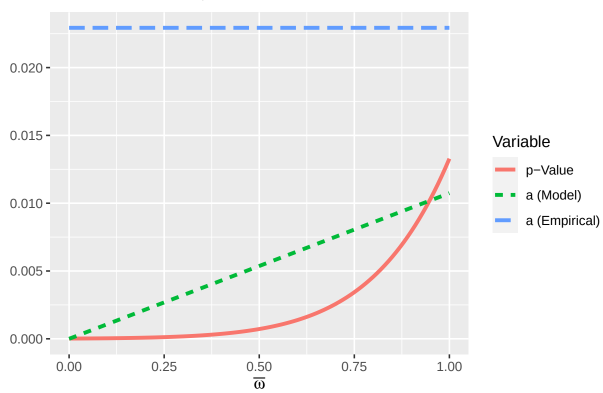


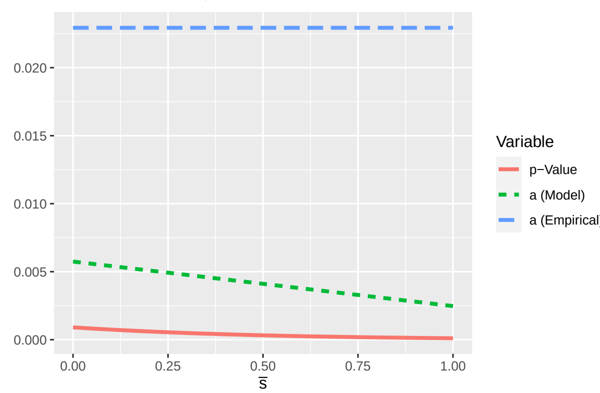
Figure IA.2: Parameter sensitivity analysis w.r.t. $\bar{\omega}$ and $\bar{s}$

The figure presents results of a sensitivity analysis of our parameters $\bar{\omega}$ (average share invested in unobserved positions) and $\bar{s}$ (average proportion of long position's beta that is hedged with short positions). We plot the empirically estimated intercept from Equation (9) as the dashed blue line. The dotted green line represents the model-implied intercept following Equation (13), varying $\bar{\omega}$ n Panels A and C, and $\bar{s}$ in Panels B and D. The p-Value of testing whether $\bar{\beta}^{\text{PBCh.}}$ is greater than 0 is plotted as the solid red line. Panels A and B focus on β's estimated on all observations. Panels C and D focus on downside β's, i.e., β's estimated on observations where $r_t^{FI} < 0$.
Increasing $\bar{\omega}$ increases the model-implied intercept. However, unrealistically high values of $\bar{\omega}$ would be needed in order to get p-Values north of conventional levels of statistical significance ($\bar{\omega} \geq 0.95$ for full-sample betas and $\bar{\omega} \geq 0.66$ for downside betas to surpass a significance level of 1%). Even for $\bar{\omega} = 1$, the empirical point estimate of a is larger than the model-implied one (for both full-sample and downside betas).
Decreasing $\bar{s}$ also increases the model-implied intercept. However, even setting $\bar{s} = 0$ still leaves the empirical estimate of a significantly larger than the model-implied one.

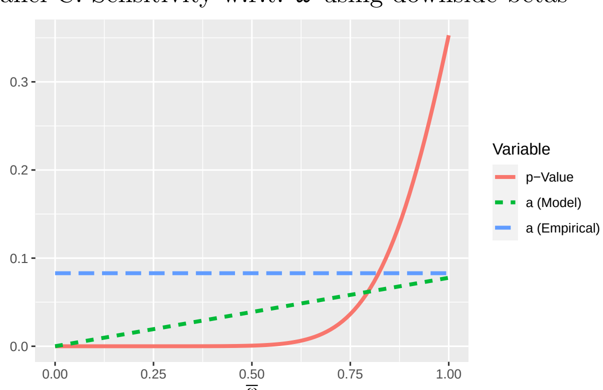
Panel A: Sensitivity w.r.t. $\bar{\omega}$



Panel B: Sensitivity w.r.t. $\bar{s}$



Panel C: Sensitivity w.r.t. $\bar{\omega}$ using downside betas



Panel D: Sensitivity w.r.t. $\bar{s}$ using downside betas

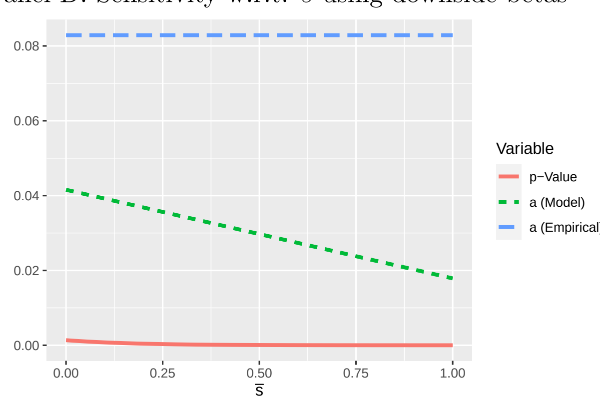
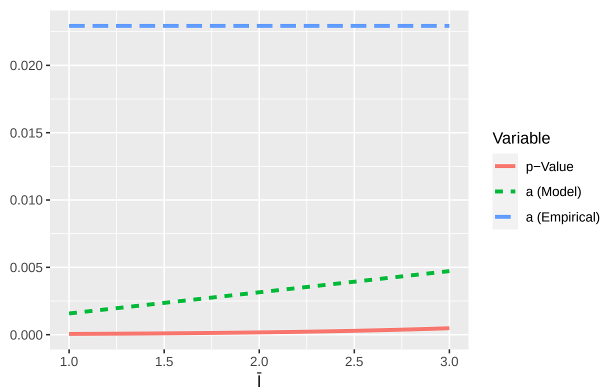


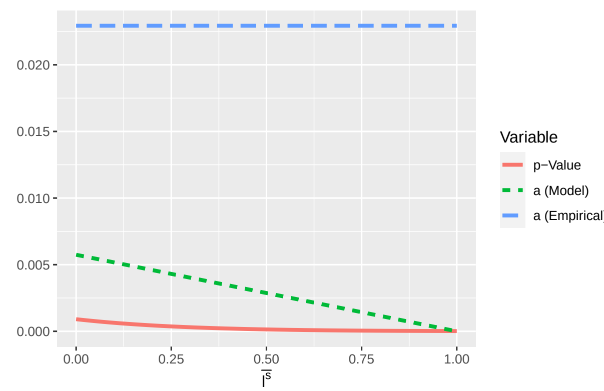
Figure IA.3: Parameter sensitivity analysis w.r.t. $\bar{\ell}$ and $\bar{\ell^s}$

The figure presents results of a sensitivity analysis of our parameters $\bar{\ell}$ (average leverage) and $\bar{\ell^s}$ (average short exposure).
We plot the empirically estimated intercept from Equation (9) as the dashed blue line. The dotted green line represents the model-implied intercept following Equation (13), varying $\bar{\ell}$ n Panels A and C, and $\bar{\ell^s}$ in Panels B and D. The p-Value of testing whether $\bar{\beta}^{\text{PBCh.}}$ is greater than 0 is plotted as the solid red line.
Panels A and B focus on β's estimated on all observations. Panels C and D focus on downside β's, i.e., β's estimated on observations where $r_t^{FI} < 0$.
Increasing $\bar{\ell}$ increases the model-implied intercept. However, even at $\bar{\ell} = 2.59$, which corresponds to the 90th percentile of hedge fund leverage reported in Barth, Hammond, and Monin (2020), the model-implied a is far from the empirically estimated one.
Decreasing $\bar{\ell^s}$ also increases the model-implied intercept. However, even setting $\bar{\ell^s} = 0$ still leaves the empirical estimate of a significantly larger than the model-implied one.

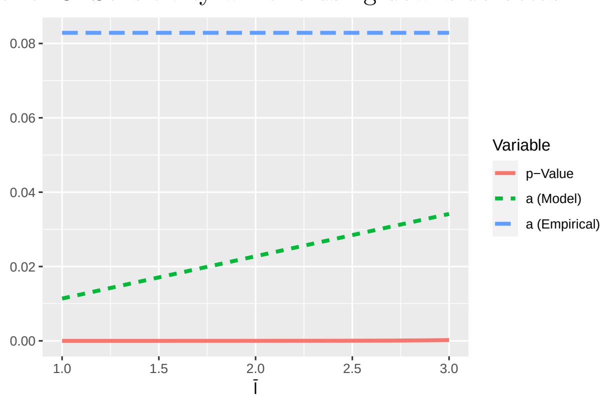
Panel A: Sensitivity w.r.t. $\bar{\ell}$



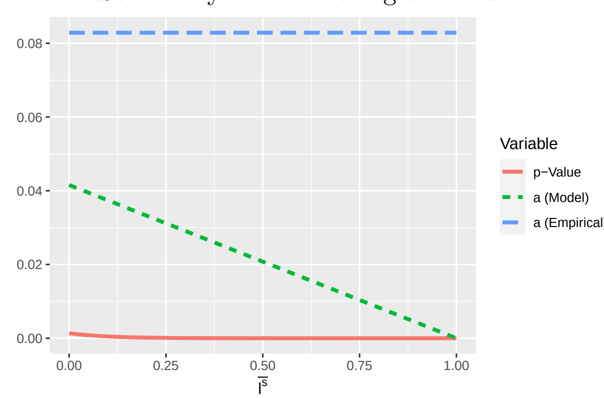
Panel B: Sensitivity w.r.t. $\bar{\ell^s}$



Panel C: Sensitivity w.r.t. $\bar{\ell}$ using downside betas



Panel D: Sensitivity w.r.t. $\bar{\ell^s}$ using downside betas



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