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Institutional Investors and Granularity in Equity Markets*

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January 1, 2021

Abstract

The U.S. equity markets are largely driven by actions of institutional investors. Using quarterly 13-F holdings, we construct the Herfindahl-Hirschman Index of institutional investor concentration as a measure of granularity. We study how granularity affects: the cross-section of returns, conditional variances and downside risk. Next, we study the impact of granularity in a demand-driven asset pricing model introduced by Koijen and Yogo (2019). We derive a decomposition of expected returns in terms of equally weighted asset demands and granularity residuals. Using this decomposition, we revisit the empirical stylized facts pertaining to granularity and asset pricing.

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1 Introduction

The U.S. equities market price process is largely driven by the information sets and actions of large institutional investors, not individual retail investors. As the majority of equity trading volume has moved toward electronic exchanges and higher frequency trading platforms, the influence of a few can have an out-sized influence on the many. This influence may be largely asymmetric in nature, with the degree of institutional impact unevenly distributed among traded names and therefore generating a cross-sectional distribution of risk. We aim to systematically study how institutional investor concentration impacts the conditional distribution of stock returns.

Our analysis touches on the notion of *granularity*. Gabaix (2011) finds that idiosyncratic movements in the production of the largest 100 firms explain about one third of the variations in output and Solow residual, suggesting that the granular composition of the economy matters. Carvalho and Gabaix (2013) take this a step further and argue that the so-called "great moderation", a significant fall in the volatility of GDP that began in the 1980's, is mostly due to a change in the fluctuations of the output of the biggest firms in the U.S. Both papers pertain to the structure of the economy. Kelly, Lustig, and Van Nieuwerburgh (2013) relate customer-supplier connectedness to firm stock market volatility.

Our paper is not about the granularity of the economy, or how it might explain economic fluctuations or firm-specific volatility. Yet, we borrow the ideas of granularity and apply them to institutional investor stock holdings and how it affects asset pricing – in particular the cross-section of stock returns. In our analysis granularity encapsulates both the concentration of the equity market investor base and how influential the investors are both individually and more broadly as a part of a dynamic network.[1]

[1] A number of papers have studied the impact of institutional investors on asset prices, including Shleifer (1986), Morck, Shleifer, and Vishny (1988), Chen, Hong, and Stein (2002), Barberis, Shleifer, and Wurgler (2005), among others. More recently, Ben-David, Franzoni, Moussawi, and Sedunov (2016) also note that the U.S. asset management industry has become increasingly concentrated and study the fact that large institutions are not equivalent to a collection of smaller independent entities. They study the impact of large institutional ownership on stock volatility and find that their presence increases price instability.

We use quarterly 13-F holdings reported by institutional investors and focus on the Herfindahl-Hirschman Index (HHI) as the measure of granularity and provide a comprehensive study of how it affects: (1) the cross-section of returns, (2) conditional variances across stocks and (3) downside risk.

Koijen and Yogo (2019) develop an asset pricing model with rich heterogeneity in asset demand across investors, designed to match institutional holdings. We adopt their framework and show via a novel simple diagnostic specification test that granularity affects institutional asset demands. The presence of this omitted factor implies that their empirical model can be improved upon and in particular study how their empirical findings change once granularity is taking into account.

We start with a decomposition of returns based on what we call granularity residuals. The model-based decomposition will allow us to reconcile and better understand the impact of HHI on the pricing of equities. Armed with improved model specifications we study the aforementioned granularity decomposition and draw comparisons with the stylized facts documented in the first part of the paper.

2 Granularity: Expected Returns, Volatility and Downside Risk

We study the quarterly 13-F holdings reported by institutional investors. We obtain institutional 13-F filings from the Thomson-Reuters Institutional Holdings Database. This database provides ownership information of institutional investment managers with assets under management of over $100 million in Section 13(f) securities. These securities, per SEC stipulations, generally include equity securities that trade on an exchange, certain equity options and warrants, shares of closed-end investment companies, and certain convertible debt securities. We also collect quarterly individual stock returns and accounting information from CRSP and COMPUSTAT, respectively. The sample period is from 1980Q1 to 2019Q1.

In addition, we collect CRSP daily stock return data for the same period and monthly Fama-French 3 factor return data are obtained through Kenneth French's website. The Pastor and Stambaugh (2003) tradable liquidity factors are obtained through WRDS also at the monthly frequency. We transform these monthly return factors into quarterly data. A more detailed analysis of the data appears in the Online Appendix B.

A casual overview of the market composition reveals that, during the 156 quarters or 39-year time period of our sample, there was an upward trend in both the number of 13-F institutional investors and their aggregate dollar holdings. The reported number of institutional investors is 467 in 1980Q1, and increases to 4420 in 2019Q1. The dollar amount held by the 13-F institutions increased from \$321 billion in 1980Q1 to \$21 trillion in 2019Q1 with several substantial drops in the early 2000s and during the global financial crisis (see Figure B.2 in Online Appendix B).

2.1 Measurement

While we witnessed a notable expansion in the institutional investor universe, we would like to examine if the market has become more concentrated. For that purpose, we identify the group of institutional investors with the largest holdings each quarter. We treat the largest 3, 5, 7, or 10 managers as one entity, and describe their associated holding characteristics vis-à-vis the universe of all 13-F institutional investor filings.[2] The analysis is conducted on a quarterly basis and Figure 1 plots the share of holdings by the largest 3, 5, 7 and 10 institutional investors. We observe that by the beginning of 2019, the 10 largest institutional investors make up 34.48% of all 13-F institution holdings. The proportion is 20.95%, 25.94%, and 29.55% for the top 3, 5, and 7 institutions, respectively. These are remarkably different from the market shares at the beginning of 1980, which are 8.30%, 11.49%, 14.27%, and 18.11% respectively for the 3, 5, 7, and 10 largest institutional investors.

To proceed with our analysis on market granularity we start by calculating the market-

[2]Market share of an individual institution is the ratio of its dollar holdings to the aggregate amount reported by the 13-F filing institutions.

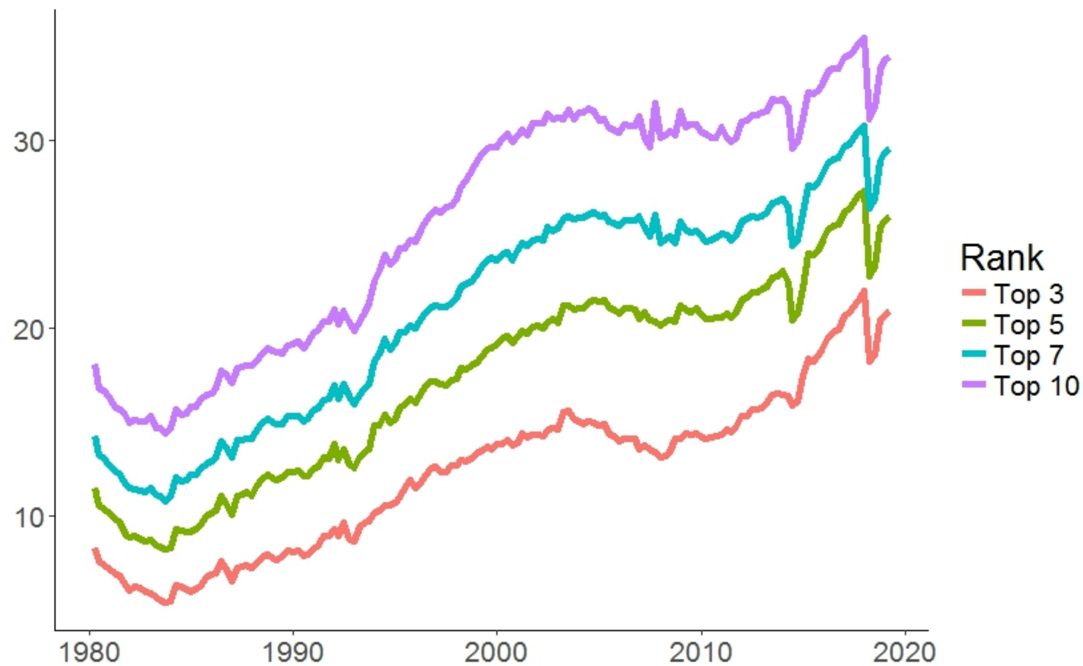


Fig. 1: Quarterly Top Institutional Investor Market Shares

wide Herfindahl-Hirschman Index (HHI), defined as:

$$HHI_t = \sum_{i=1}^{N_t} s_{it}^2, \tag{1}$$

where s_{it} is the market share of institution i during quarter t, and N_t is the total number of institutional investors during quarter t. Figure 2, which displays the quarterly aggregate HHI measures, reveals that market concentration was rising steadily until the financial crisis. The market became less concentrated during the financial crisis, but has surpassed its previous level of concentration once the crisis ended. Note that due to the large number of existing institutions, the magnitude of the HHI index remains small.

To form portfolios we compute a similar HHI measure that depicts the dispersion of institutional ownerships at the individual stock level. Namely, for each listed security e, we catalog the investment managers that are long in the stock. We record the fractions of these

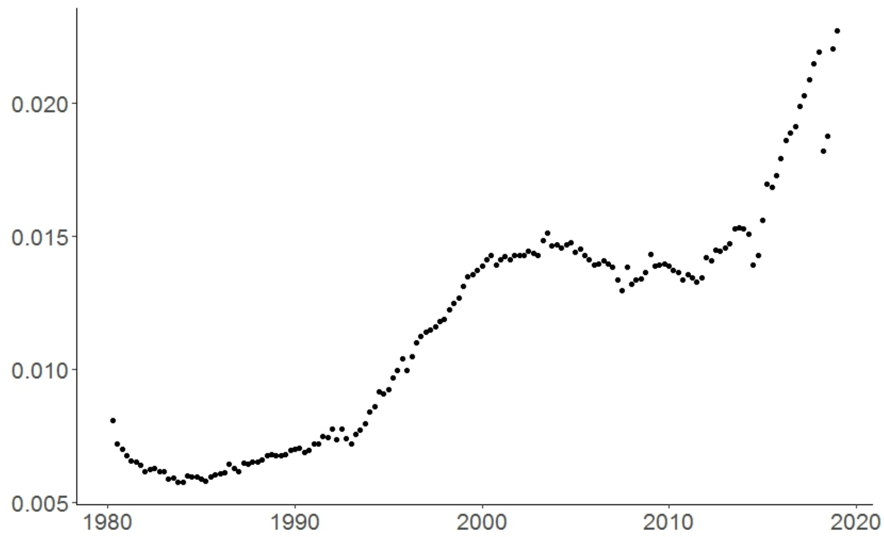


Fig. 2: Quarterly Aggregate HHI

holding sizes relative to the combined holdings of the qualified 13-F institutions, namely:

$$H_t^e = \sum_{i=1}^{N_t^e} [s_{it}^e]^2, \qquad e = 1, \ldots, E_t \tag{2}$$

where s_{it}^e is the market share of institution i for stock e at time t and N_t^e is the total number of institutional investors during quarter t holding $e = 1, \ldots, E_t$, where the latter is the total of equities in quarter t. For instance, the HHI of a stock is equal to 1 if it is held by only one investment manager at the time of the 13-F filings. Alternatively, 100 institutional investors each possessing an equal amount of a stock generates an HHI value of 0.01. The latter signifies a more diverse profile of stock ownership.

2.2 Empirical Conditional Moments

We consider sorting stocks by ownership concentration H_t^e (see Online Appendix B.1 for details and portfolio summary statistics) and start with equally-weighted portfolios. These portfolios are long in broad ownership stocks and short in stocks held by few institutional investors. Table 1 reports descriptive statistics of the low minus high (LMH) HHI portfolios.

The LMH portfolios delivers on average a 5.6% annualized excess return, significantly different from 0 at the 1% level. The median return is higher at 7.8% although the distribution is negatively skewed and has a standard deviation of roughly 11%.

Table 1: Annualized HHI Low-High Portfolio Returns

Mean	Median	Std. Dev.	Skew	Kurt.	25 %	75 %
5.57	7.76	11.04	-5.99	57.33	-0.75	14.25

Notes: This table shows summary statistics of annualized percentage returns from the Low-Minus-High (LMH) portfolio we constructed. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

Conditional Means – Linear Factor Models How much are HHI portfolio returns explained by standard asset pricing factors? To answer this question we consider a number of factor model specifications, where F_t will denote the factor(s). In particular, we consider: (a) the Fama-French 3 Factor model ($Rm-Rf$, SMB, HML), (b) Fama-French 3 Factor + Pastor-Stambaugh tradable liquidity (the latter denoted LIQ) and finally (c) Fama-French 3 Factors, Pastor-Stambaugh tradable liquidity and the first principle component of $[HHI]_{i,t}$, denoted $PC - HHI$. We start with the correlation across the factors being considered,

Table 2: Linear Factor Correlations

	Rm-Rf	SMB	HML	Liq	HHI
Rm-Rf	1.00				-
SMB	0.46	1.00			
HML	-0.20	-0.01	1.00		
Liq	-0.07	-0.03	-0.01	1.00	
HHI	-0.07	0.20	0.08	0.18	1.00

Notes: This table shows correlations between (1) Fama-French 3 factors, i.e. market risk, size, and book-to-market, (2) Pastor-Stambaugh tradable liquidity, and (3) first principle component of HHI. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

which appear in Table 2. Of particular interest is the first PC-HHI. It has a small negative correlation with the excess return on the market portfolio, and maximal correlation of only 20% with the SMB portfolio. This means that the breadth of institutional ownership is somewhat related to the small cap premium, but that relationship is weak. The same applies to the liquidity factor, with second largest correlation of 18%. The main take-away is that the tradable liquidity factor and the first principle component of HHI are not highly correlated.

Next, we estimate linear factor models of the following form using GMM for the 5 HHI-sorted portfolios at the quarterly frequency from 1980Q1-2019Q1 ($i = 1, ..., 5$, $t = 1, ..., 157$):

$$\begin{aligned} R_{i,t} &= \alpha_i + F_t'\beta_i + \epsilon_{i,t} \\ E[R_{i,t}] &= \lambda'\beta_i + e_i \end{aligned} \tag{3}$$

The summary results for equally-weighted HHI portfolios are reported in Table 3.[3] It appears from Table 3 that none of the proposed factor models sufficiently describe the cross-section of equally-weighted HHI portfolio returns, as evidenced by the rejection of the Gibbons, Ross, and Shanken (1989) test and over-identification J-tests. Moreover, the HHI LMH α is of similar magnitude to its annualized unconditional average of 5.6%. Overall these results also hold to a lesser degree for value-weighted HHI portfolios.

Table 3: HHI Portfolios Unconditional Linear Factor Models

	CAPM	FF3	FF3+Liq	q-Factor
HHI LMH α	4.91***	5.51***	6.03***	5.08**
	(1.92)	(1.86)	(1.89)	(2.58)
GRS p-value (%)	< 0.01	< 0.01	< 0.01	< 0.01
J-stat p-value (%)	4.68	< 0.01	< 0.01	< 0.01

Notes: This table shows the HHI LMH portfolio α (annualized percentage) as well as the p-values for the Gibbons, Ross, and Shanken (1989) test (GRS) and GMM J-statistic. The tests respectively come from a time-series and 2-step GMM estimation of the following unconditional linear factor models using the HHI-sorted portfolios: CAPM, Fama-French three-factor (FF3), Fama-French three-factor and Pastor-Stambaugh tradable liquidity factor (FF3+Liq), and the Hou-Xue-Zhang q-factor (Hou, Xue, and Zhang (2015)). Our quarterly sample starts in 1980Q1 and ends in 2014Q4. Newey and West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Conditional Volatility It was noted that Ben-David, Franzoni, Moussawi, and Sedunov (2016) study whether large institutional ownership has a significant impact on individual

[3] Loadings and prices of risk for the HHI portfolios appear in Table B.5 in Online Appendix Section B.4. We also implemented the standard Fama and MacBeth (1973) procedure, which yields very similar results. We get almost identical beta estimates and the prices of risk are fairly close. Detailed results are available upon request.

stock volatility. They conjecture as a potential channel for this effect that large institutions generate higher price impact than smaller institutions. They provide empirical supporting evidence and argue that the effect of large institutions on volatility is unlikely to be related to improved price discovery, because the stocks owned by large institutions exhibit stronger price inefficiency.

We take a slightly different route and estimate GJR-GARCH(1,1) models at the quarterly frequency for the high-HHI and low-HHI portfolios. In particular, we estimate the following model: $r_{i,t} = \mu + \sigma_{i,t}\epsilon_{i,t}$, with $\sigma^2_{i,t} = a_0 + a_1\sigma^2_{i,t-1} + b_1\epsilon^2_{i,t-1} + c_1 I(\epsilon_{i,t-1} < 0)\epsilon^2_{i,t-1}$.

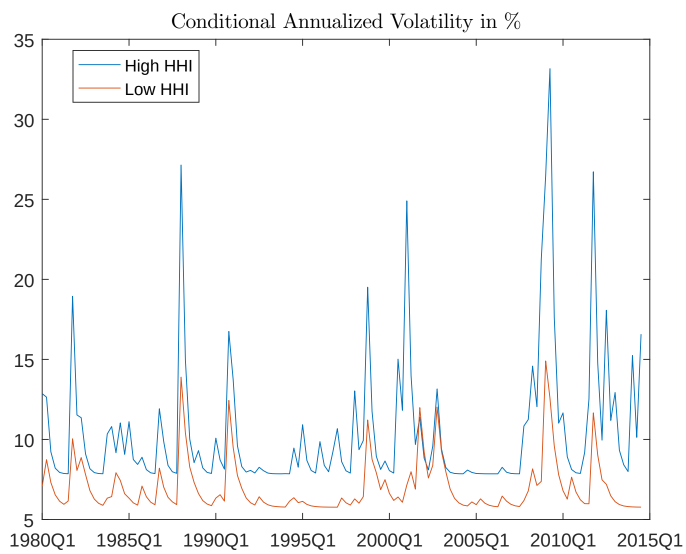


Fig. 3: Conditional Volatility High versus Low HHI Portfolio

The estimated conditional volatilities are plotted in Figure 3. We observe a clear level shift in the volatilities between the high versus low HHI portfolios, suggesting that there is a potential difference in both the average level of volatility as well as the volatility of volatility. The volatility of the high-HHI portfolio is substantially higher, sometimes three to four times the level of annualized volatility of the low-HHI portfolio. How much is this due to say small firm effects or other factors affecting the overall level of volatility? To investigate this further we regress the estimated conditional volatilities on each portfolio's HHI value, namely for i

Table 4: Conditional Volatility Regressions – Quarterly

	Constant	$\hat{\sigma}^2_{i,t-1}$	HHI	LIQ	SMB	R^2
1 (high HHI)	−0.0033	0.4453***	0.0054*			0.2158
	(0.0028)	(0.1571)	(0.0030)			
5 (low HHI)	0.0011**	0.4128***	−0.0079			0.1750
	(0.0005)	(0.0575)	(0.0100)			
1 (high HHI)	−0.0035	0.4450***	0.0056	−0.0013		0.2162
	(0.0031)	(0.1408)	(0.0034)	(0.0075)		
5 (low HHI)	0.0011**	0.4222***	−0.0079	−0.0010		0.1800
	(0.0005)	(0.0705)	(0.0097)	(0.0016)		
1 (high HHI)	−0.0063**	0.5029***	0.0085**	−0.0023	−0.0256***	0.3221
	(0.0032)	(0.1394)	(0.0035)	(0.0066)	(0.0066)	
5 (low HHI)	0.0010**	0.5198***	−0.0070	−0.0013	−0.0062***	0.2954
	(0.0005)	(0.0724)	(0.0095)	(0.0015)	(0.0014)	

Notes: This table shows estimation results for the regressions in Online Appendix equation (C.5). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Newey and West (1987) standard errors appear in parentheses.

= 1 and 5 we estimate the following:

$$\begin{aligned}
\hat{\sigma}^2_{i,t} &= b_{i,0} + b_{i,1}\hat{\sigma}^2_{i,t-1} + b_{i,2}HHI_{i,t} + v_{i,t} \qquad (4)\\
\hat{\sigma}^2_{i,t} &= b_{i,0} + b_{i,1}\hat{\sigma}^2_{i,t-1} + b_{i,2}HHI_{i,t} + b_{i,3}Liq_t + v_{i,t}\\
\hat{\sigma}^2_{i,t} &= b_{i,0} + b_{i,1}\hat{\sigma}^2_{i,t-1} + b_{i,2}HHI_{i,t} + b_{i,3}Liq_t + b_{i,4}SMB_t + v_{i,t}
\end{aligned}$$

where $\hat{\sigma}^2_{i,t}$ are fitted conditional volatilities from the GJR-GARCH(1,1) estimation.[4] The results appear in Table 4. We find that for high-HHI portfolios, increasing investor concentration is associated with higher conditional volatilty, even after controlling for liquidity and size. Conversely, the impact of HHI is statistically insignificant across all specifications for the low-HHI portfolio. In short, marginal increases in investor concentration are associated with higher conditional volatiltiy for stocks with high investor concentration. In other words, the impact of HHI on conditional volatility is asymmetric with respect to the level of HHI.

In addition, we estimate GJR-GARCH(1,1) models at the monthly frequency and retain these monthly conditional volatility estimates for the first month in each calendar quarter

[4]The lagged dependent variable, being an estimated proxy, may be a cause of concern as it produces a bias for $b_{i,1}$ and the other parameters. Some experimentation with instrumental variables reveals that the concern is inconsequential for our hypothesis of interest.

(January, April, July, and October). We do this to sharpen our focus on the potential impact of HHI immediately following its filing each quarter. We then estimate the same regression specifications and find that the impact of HHI on conditional volatility is similar. Increasing investor concentration is associated with higher conditional volatility in high-HHI portfolios. In addition the point estimates on HHI for the high-HHI portfolios are slightly larger than the quarterly specification, an indication that the impact of HHI each period may dissipate towards the end of the quarter. Equally-weighted portfolio results appear in Table 5. Overall we find that the results of Ben-David, Franzoni, Moussawi, and Sedunov (2016) are sufficiently strong to prevail at the portfolio return level.

Table 5: Conditional Volatility Regressions – Monthly

	Constant	$\hat{\sigma}^2_{i,t-1}$	HHI	LIQ	SMB	R^2
1 (high HHI)	−0.0060	0.4189***	0.0096**			0.2106
	(0.0043)	(0.1308)	(0.0048)			
5 (low HHI)	0.0047***	0.1234	−0.0409			0.0246
	(0.0017)	(0.1137)	(0.0353)			
1 (high HHI)	−0.0062	0.4170***	0.0098*	−0.0017		0.2107
	(0.0045)	(0.1317)	(0.0050)	(0.0073)		
5 (low HHI)	0.0048***	0.1314	−0.0438	0.0067		0.0326
	(0.0018)	(0.1118)	(0.0359)	(0.0047)		
1 (high HHI)	−0.0065	0.4147***	0.0101**	−0.0014	−0.0093	0.2136
	(0.0045)	(0.1342)	(0.0051)	(0.0074)	(0.0073)	
5 (low HHI)	0.0044***	0.1587	−0.0391	0.0062	0.0123	0.0487
	(0.0017)	(0.1038)	(0.0345)	(0.0048)	(0.0107)	

Notes: This table shows estimation results for the regressions in (C.5). Conditional volatilities are produced for the first mont in each calendar quarter. Quarterly sample starts in 1980Q1 and ends in 2019Q1. Newey and West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

We also compute risk-neutral variances from a large panel of options data and follow the methodology in Conrad, Dittmar, and Ghysels (2013) and report on the results in Section C.3. The evidence is largely in line with the results using cash market risk measures. This suggests that the effect of HHI also appears in the pricing of derivative contracts.

Downside Risk Arguably the strongest impact of institutional investor concentration appears to be in downside risk. We start with estimating conditional quantiles. The model we rely on to characterize downside risk is the conditional autoregressive value at risk (CAViaR)

Fig. 4: Conditional Quantile Estimates HHI Portfolios 5% Left Tail

model introduced by Engle and Manganelli (2004). The functional form is

$$q_t(\theta) = \beta_1 + \beta_2 q_{t-1}(\theta) + \beta_3 |r_{t-1}| + \epsilon_{t,\theta}, \tag{5}$$

where $q_t(\theta)$ denotes the conditional quantile associated with probability level θ. We look at $\theta = .05$, i.e. the left 5% tail. We compute quantiles for each of the HHI portfolios, and the results for the highest HHI and the lowest HHI portfolio appear in Figure 4. We clearly see that the high-HHI portfolio has a more pronounced left tail - with values as low as -15%. In fact, the high-HHI quantiles are remarkably lower than the ones from the low-HHI portfolio at almost all times. The spread between the high-HHI and low-HHI conditional percentiles is typically on the order of 4 to 5 %. We project the estimated quantiles again on the same

Table 6: Regression of Conditional Quantile on HHI

	Constant		HHI		LIQ	SMB	R^2
1 (high HHI)	0.0622	*	-0.1614	***			0.2039
	(0.0262)		(0.0272)				
5 (low HHI)	-0.0480	***	0.1214				0.0014
	(0.0131)		(0.2785)				
1 (high HHI)	0.0630	*	-0.1624	***	0.0045		0.2042
	(0.0265)		(0.0276)		(0.0217)		
5 (low HHI)	-0.0474	***	0.1177		-0.0237		0.0063
	(0.0131)		(0.2789)		(0.0286)		
1 (high HHI)	0.0680	*	-0.1678	***	0.0060	0.0361	0.2138
	(0.0267)		(0.0279)		(0.0217)	(0.0279)	
5 (low HHI)	-0.0475	***	0.1183		-0.0236	0.0032	0.0064
	(0.0132)		(0.2800)		(0.0288)	(0.0371)	

Notes: This table shows results for the estimated regressions in equation (6). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Newey and West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

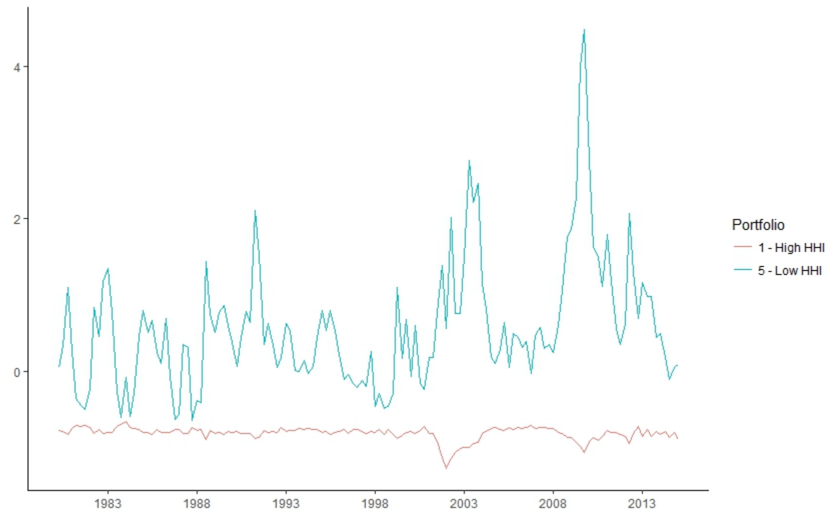
variables, namely for $i = 1$ and 5 we run the following regressions:

$$\begin{aligned} q_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI_{i,t-1} + v_{i,t} \qquad (6) \\ q_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI_{i,t-1} + b_{i,2}Liq_{t-1} + v_{i,t} \\ q_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI_{i,t-1} + b_{i,2}Liq_{t-1} + b_{i,3}SMB_{t-1} + v_{i,t} \end{aligned}$$

The results appear in Table 6. We find overwhelming evidence that downside risk is driven by the HHI measure in the high but not the low portfolio. This means that stocks with only a few institutional investors feature an incremental downside risk. Note also how the R^2 of the regressions increase for all the high-HHI quantiles, meaning that HHI explains a substantial part of the variation in downside risk.

To account for volatility when addressing downside risk, we filter the returns through a standard GARCH(1, 1) and a GJR-GARCH(1, 1) model separately. These two scenarios reflect a fair representation of both symmetric and asymmetric GARCH models. We then proceed to use the filtered return series to re-estimate the 5% conditional quantiles, having controlled for conditional volatility. It remains that the high-HHI portfolio is subject to a higher degree of downside risk, as indicated by the left tails of portfolio returns. This can

Fig. 5. Conditional Quantile Estimates HHI Portfolios 5% Left Tail - GARCH(1, 1) Filtered



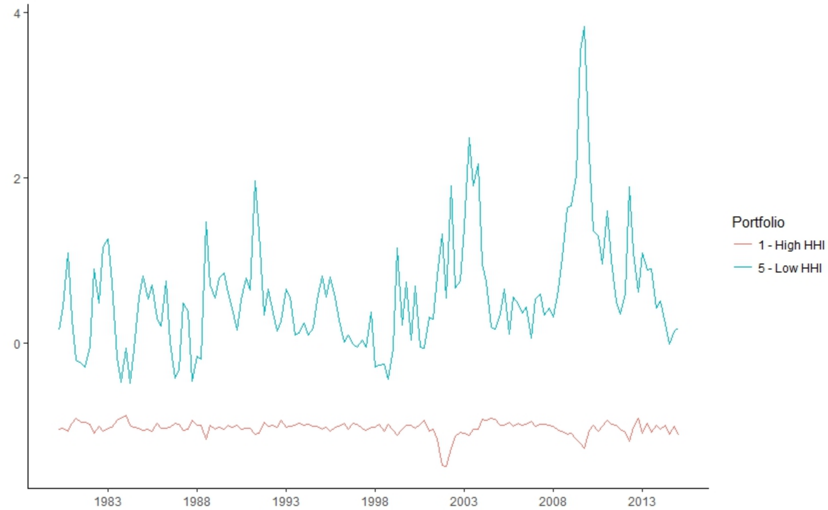
be shown from Figure 5 and Figure 6, and our findings hold in both cases.

2.3 Downside Risk and Top Players

What happens to our findings if we separate the largest asset managers each quarter from the rest? Do our findings reported in the previous section still hold? This question is of interest because of several reasons. A first reason is that we can view such an exercise as a robustness check, verifying that our results are not simply driven by a single or a few large institutional investors. Second, there have been discussions about whether giant U.S. money managers should be viewed as systemically important financial institutions (so called SIFIs) and be subjected to increased regulatory supervision. For example, according to financial press articles (see e.g. *Wall Street Journal*, June 1, 2015) both BlackRock and Fidelity have insisted to international regulators that they do not pose threats to the financial system should they collapse. It was reported that they sent letters to the Financial Stability Board in Basel, Switzerland, outlining why Fidelity and BlackRock disagree with efforts to identify money managers that could be subject to stricter oversight because of the risks they pose.

In this subsection, we examine the impact of top 3, top 5, and top 10 institutional in-

Fig. 6. Conditional Quantile Estimates HHI Portfolios 5% Left Tail - GJR-GARCH(1, 1) Filtered



vestors. It is important to note that these groups of institutional investors are heterogeneous throughout our sample, as none has appeared consistently as a top player. We are interested in the impact that the top institutions potentially my have on the entire market. We rank the institutions each quarter by their dollar holdings, and study the top 3, top 5, and top 10 institutions as combined entities. Throughout the sample period, the majority of the holdings of the largest institutions are characterized by a low market concentration ratio. The proportion of aggregate holdings that belong to the lowest-HHI portfolio 5 is on average around 90%, and the ratio remains within a fairly stable range based on results reported in Table 7.

We examine downside risk using a variation of equation (6). Specifically, we perform the regressions below:

$$\begin{aligned} q_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI(k)_{i,t-1} + b_{i,2}HHI(-k)_{i,t-1} + v_{i,t} \qquad (7) \\ q_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI(k)_{i,t-1} + b_{i,2}HHI(-k)_{i,t-1} + b_{i,3}Liq_{t-1} + v_{i,t} \\ q_{i,t}(.05) &= b_{i,0} + b_{i,1}HHI(k)_{i,t-1} + b_{i,2}HHI(-k)_{i,t-1} + b_{i,3}Liq_{t-1} + b_{i,4}SMB_{t-1} + v_{i,t} \end{aligned}$$

Table 7: Top Institutions Holding Decomposition

HHI Portfolio	1	2	3	4	5
Top 3					
Dollar Holdings (mean %)	0.21	0.38	1.37	7.61	90.42
(max %)	5.75	1.83	3.97	14.91	96.43
(min %)	0	0.02	0.24	3.06	80.81
Number of Stocks (mean %)	3	9	19	31	38
Top 5					
Dollar Holdings (mean %)	0.35	0.45	1.37	7.73	90.10
(max %)	4.35	1.60	4.59	12.91	95.24
(min %)	0	0.02	0.24	3.54	82.83
Number of Stocks (mean %)	3	10	20	31	36
Top 10					
Dollar Holdings (mean %)	0.30	0.48	1.55	7.73	89.94
(max %)	2.76	1.32	4.48	13.61	95.15
(min %)	0	0.02	0.28	3.76	84.77
Number of Stocks (mean %)	4	11	22	30	32

Notes: This table shows summary statistics of percentage holdings in each portfolio for the largest 3, 5, and 10 institutions. The proportions are measured with respect to dollar amount and number of stocks. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

where k = 3, 5, 10. The following decomposition identity holds for all k and all portfolios:

$$HHI_{i,t} = HHI(k)_{i,t} + HHI(-k)_{i,t} = \sum_{j \in Top-k} s_{j,t}^2 + \sum_{l \notin Top-k} s_{l,t}^2.$$

Through this approach we can isolate the effect of concentration on downside risk in the holdings of the top institutions. In general, the largest institutions contribute more to the concentration in low-HHI portfolios. This is consistent with the empirical fact that these institutions are more likely to hold equities with lower degrees of concentration as part of their portfolios.

We consolidate portfolios 1 and 2 into a high-HHI group and portfolios 4 and 5 into a low-HHI group and report results for the combined portfolios. The results appear in Table 8 which features three panel for respectively the top 3, 5 and 10 institutional investors as a separate entity in the HHI calculations.

There is much similarity between the average impact of top 3, 5 and 10 HHI on the high-HHI's portfolio's conditional quantiles. In fact the coefficients are quite stable across

Table 8: Regression of Conditional Quantile on Decomposed HHI

Panel A: Top 3 Insitutions

	Constant		HHI_3		HHI_{-3}		LIQ	SMB	R^2	$HHI_3 = HHI_{-3}$
High HHI	0.0059		-0.1374	**	-0.0978	***			0.3508	0.368
	(0.0071)		(0.0465)		(0.0081)					
Low HHI	-0.0459	***	1.3270	**	-0.1863	***			0.0802	0.0005***
	(0.0037)		(0.4116)		(0.0386)					
High HHI	0.0062		-0.1428	**	-0.0975	***	-0.0252		0.3532	0.3064
	(0.0071)		(0.0468)		(0.0081)		(0.0250)			
Low HHI	-0.0455	***	1.2884	**	-0.1834	***	-0.0160		0.0821	0.0008***
	(0.0037)		(0.4151)		(0.0388)		(0.0214)			
High HHI	0.0064		-0.1421	**	-0.0980	***	-0.0244	0.0261	0.3547	0.3209
	(0.0072)		(0.0468)		(0.0081)		(0.0251)	(0.0321)		
Low HHI	-0.0456	***	1.3010	**	-0.1837	***	-0.0161	-0.0074	0.0823	0.0008***
	(0.0037)		(0.4185)		(0.0389)		(0.0215)	(0.0276)		

Panel B: Top 5 Insitutions

	Constant		HHI_5		HHI_{-5}		LIQ	SMB	R^2	$HHI_5 = HHI_{-5}$
High HHI	0.0059		-0.1338	**	-0.0977	***			0.3509	0.359
	(0.0071)		(0.0418)		(0.0081)					
Low HHI	-0.0514	***	1.6716	***	-0.2315	***			0.1135	0***
	(0.0040)		(0.3718)		(0.0402)					
High HHI	0.0063		-0.1384	**	-0.0973	***	-0.0252		0.3533	0.3001
	(0.0071)		(0.0420)		(0.0081)		(0.0250)			
Low HHI	-0.0511	***	1.6441	**	-0.2291	***	-0.0108		0.1144	0***
	(0.0041)		(0.3760)		(0.0405)		(0.0211)			
High HHI	0.0064		-0.1368	**	-0.0978	***	-0.0243	0.0251	0.3547	0.3261
	(0.0072)		(0.0421)		(0.0081)		(0.0251)	(0.0322)		
Low HHI	-0.0511	***	1.6493	**	-0.2291	***	-0.0109	-0.0054	0.1145	0***
	(0.0041)		(0.3776)		(0.0406)		(0.0211)	(0.0270)		

Panel C: Top 10 Insitutions

	Constant		HHI_{10}		HHI_{-10}		LIQ	SMB	R^2	$HHI_{10} = HHI_{-10}$
High HHI	0.0058		-0.1268	***	-0.0969	***			0.3514	0.3007
	(0.0069)		(0.0306)		(0.0079)					
Low HHI	-0.0506	***	1.1625	***	-0.2686	***			0.0849	0.0003***
	(0.0044)		(0.3448)		(0.0533)					
High HHI	0.0059		-0.1278	**	-0.0964	***	-0.0235		0.3535	0.2767
	(0.0069)		(0.0306)		(0.0079)		(0.0249)			
Low HHI	-0.0502	***	1.1337	**	-0.2640	***	-0.0170		0.0870	0.0004***
	(0.0045)		(0.3469)		(0.0537)		(0.0213)			
High HHI	0.0059		-0.1260	***	-0.0968	***	-0.0227	0.0237	0.3548	0.3174
	(0.0070)		(0.0308)		(0.0080)		(0.0249)	(0.0323)		
Low HHI	-0.0502	***	1.1350	**	-0.2641	***	-0.0170	-0.0019	0.0870	0.0004***
	(0.0045)		(0.3480)		(0.0538)		(0.0214)	(0.0274)		

Notes: This table shows results for the estimated regressions in equation (7). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. The last column records p-values from testing whether coefficients $HHI_k = HHI_{-k}$, k = 3, 5, 10.

the three panels. The slope of $HHI(k)_{i,t}$ versus that of $HHI(-k)_{i,t}$ is roughly 33 % higher in magnitude in absolute terms meaning that the top institutional investors have a larger (negative) impact on downside risk. Another interesting phenomenon that transpires from the same table is that the top investors have a *positive* impact on the downside risk of the low-HHI portfolio, while the remaining investors still have a negative impact. The coefficients on HHI(k) for the low-HHI portfolio are significantly positive and tend to be larger in magnitude than the ones on HHI(-k), which in contrast are significantly negative. This means that top investors make widely held stock safer assets even when we control of SMB and liquidity. Overall, the low-HHI portfolio tends to be impacted more by the holdings of the top institutions.

2.4 Robustness

Next, we report a number of robustness checks - details appearing in the Online Appendix. In Online Appendix Section B.3 we calculate a liquidity-risk adjusted excess returns. The LMH portfolio returns are quite similar to those reported in Table 1. This suggests that liquidity is not a critical component – although this claim is revisited more thoroughly in the next subsection.

In Online Appendix D we explore the value-weighted HHI portfolios. The results reported in Online Appendix Table D.1 reveal that the HHI LMH spread is not as impressive with value-weighted portfolios. It has a mean of 76 basis points and is not significant. Hence, the findings reported in Table 1 are not robust in terms of a value- versus equally-weighted portfolio scheme. In contrast, almost all of the other findings reported in the rest of the paper are robust to the choice of portfolio weighting scheme. For example, the GJR-GARCH(1,1) model estimates with quarterly returns for the high-HHI and low-HHI portfolios appear in Online Appendix Section D for value-weighted portfolios. The results are similar to those reported in the main body of the paper. Moreover, we find that the impact of HHI on conditional volatility is asymmetric with respect to the level of HHI. This is also true for value-weighted portfolios (see Table D.4). The GJR-GARCH(1,1) model estimates at the monthly frequency for value-weighted portfolios appear in Table D.5 and they also confirm the results of Ben-David, Franzoni, Moussawi, and Sedunov (2016). Figure D.2, covering value-weighted portfolios, features different patterns for the quantiles but a similar spread between high- and low-HHI portfolios.

Since downside risk is quite affected by the recent financial crisis, we also report for the purpose of robustness in a separate Online Appendix Section E results for a pre-crisis sample. Those results indicate that our findings are not driven by the financial crisis. Moreover, our top player results are not driven by the extraordinary events which took place during the stock market rout following the subprime mortgage crisis - an observation relevant regarding the work by Massa, Schumacher, and Wang (2015) whose event study focuses on an important merger in the midst of the financial crisis.

The results regarding value-weighted portfolios, reported in section D, do not support as much the differential impact of top players, at least not for the high-HHI portfolios. Instead, top institutional investors do impact negatively (instead of positively) the low-HHI value-weighted return portfolios and they do so in a disproportionate fashion (see Table D.7 for further details). Ironically, when we look at the pre-crisis sample (see Table D.9) we see again that the downside risk for high-HHI portfolios is adversely (and statistically significantly) affected by the top 3, 5 and 10 institutional investors, similar to the findings reported with equally-weighted return portfolios.

Additional results regarding top players are reported in Online Appendix section C. In particular, we extend our analysis to include manager-specific information at the stock level, and investigate whether decomposing HHI along investor characteristics has an impact on downside risk. We use Brian Bushee's institutional investor classification data to add institutional type and classification at the by-stock/by-year level.[5] As in our analysis of the impact of top institutions, we independently decompose HHI across the factor

[5]Data located at: `http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html`

variables of institutional type and classification: $HHI_{i,t} = \sum_{class_t} HHI(class_t)_{i,t}$, where $HHI(class_t)_{i,t} = \sum_{j \in class_t} s^2_{j,t}$ (see aforementioned Online Appendix section for details on data construction, summary statistics, and analysis details). We present results there for conditional volatility regressions in Tables C.6 and C.7, but the main takeaway holds across our different risk measures – no specific HHI by-type or by-classification measure has a statistically significant impact on risk. We conclude that neither an investors type nor classification has a significant bearing on HHI's impact on risk.

Finally, in Online Appendix section C.2 we also consider (1) quarterly dynamic quantile regression models and (2) quantile regression models of the type reported in Table 5. Neither modifications alter the conclusions - in fact they reinforce the findings reported here.

3 Granularity and Demand-based Asset Pricing

Having documented the impact of granularity on expected equity returns, volatility and downside risk, we now turn our attention to an asset pricing model driven by institutional investor demand, i.e. the model introduced by Koijen and Yogo (2019) (henceforth KY).

We start with a decomposition of returns based on what we call granularity residuals. The model-based decomposition will allow us to better understand the impact of HHI on the pricing of equities. To empirically implement the decomposition, we need to revisit the functional specification of the institutional asset demand functions. The first feature of interest to us regarding the KY model is to note that in building their model, the authors stay away from return variables as drivers of equity demand schedules because they could violate their identifying assumption that characteristics other than price are exogenous to latent demand. Using lagged HHI fits the framework of Koijen and Yogo (2019), however. We therefore propose an easy specification test to see whether indeed lagged HHI affects institutional demand schemes, and therefore is an omitted variable in the original KY model specification. We find this to be the case.

Armed with improved model specifications we study the aforementioned granularity decomposition and draw comparisons with the stylized facts covered in the previous section.

3.1 A Granularity Decomposition of Returns

In the KY model there are N financial assets indexed by $n = 1, \ldots, N$.[6] Let $S_t(n)$ be the number of shares outstanding of asset n at date t. Let $P_t(n)$ and $D_t(n)$ be the price and dividend per share for asset n at date t. Then $ME_t(n) = P_t(n)S_t(n)$ is market equity at date t. Lowercase letters denote the logarithm of the corresponding uppercase variables. The financial assets are held by I investors, indexed by $i = 1, \ldots, I$. Each investor i allocates wealth $\mathbf{A}_{i,t}$ at date t across assets in its investment universe $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$ and an outside asset. For each asset n we have that $\mathrm{ME}_t(n) = \sum_{i=1}^{I} \mathbf{A}_{i,t} w_{i,t}(n)$ which can be rewritten in log and vector notation as:

$$\mathbf{p} = f(\mathbf{p}) = \log\left[\sum_{i=1}^{I} \mathbf{A}_i \mathbf{w}(\mathbf{p})\right] - \mathbf{s} \tag{8}$$

Proposition 2 of KY states that $f(\mathbf{p})$ has under suitable regularity conditions a unique fixed point which provides the solution to the market clearing price. Next we consider $\mathrm{ME}_t(n)$ and define the following decomposition:

$$\begin{aligned} \mathrm{ME}_t(n) &= \sum_{i=1}^{I} \mathbf{A}_{i,t} w_{i,t}(n) \\ &= \underbrace{\frac{1}{I}\sum_{i=1}^{I} \mathbf{A}_{i,t}}_{\text{EW}} + \underbrace{\sum_{i=1}^{I} \mathbf{A}_{i,t}(\frac{1}{I} - w_{i,t}(n))}_{\text{Granularity residuals}} \end{aligned} \tag{9}$$

where EW refers to equal weights and the term granularity residuals was coined by Gabaix (2011).[7] Now since $\mathrm{ME}_t(n) = P_t(n) \times S_t(n)$ and $S_t(n)$ is roughly constant across time, this

[6] In Appendix A we provide a summary of the Koijen and Yogo (2019) model.

[7] Note that we take $1/I$ as benchmark as this corresponds to HHI equal or close to zero for I large.

means that we can also think in terms a decomposition of price movements, namely for each t and each asset n :

$$\begin{aligned} P_t(n) &= \frac{1}{S(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t}w_{i,t}(n) \qquad (10) \\ &= \frac{1}{IS(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t} + \frac{1}{S(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t}(\frac{1}{I} - w_{i,t}(n)) \\ &= \frac{1}{IS(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t}\left[1 + \frac{\frac{1}{S(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t}(\frac{1}{I} - w_{i,t}(n))}{\frac{1}{IS(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t}}\right] \end{aligned}$$

Let $EW_t(n) \equiv \frac{1}{IS(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t}$ and let $GR_t(n) \equiv \frac{1}{S(n)}\sum_{i=1}^{I}\mathbf{A}_{i,t}(\frac{1}{I} - w_{i,t}(n))$. Using lower case expressions for log transforms we can write this as:

$$\begin{aligned} \log P_t(n) = p_t(n) &= ew_t(n) + \log\left[1 + \frac{GR_t(n)}{EW_t(n)}\right] \\ &= ew_t(n) + \log\left[1 + \exp\left[gr_t(n) - ew_t(n)\right]\right] \\ &\approx k + ew_t(n) + (1-\rho)\left[gr_t(n) - ew_t(n)\right] = k + \rho ew_t(n) + (1-\rho)gr_t(n) \end{aligned}$$

where in the last expression we use the Campbell and Shiller (1988) approximation with: $\rho = [1 + \exp\left[\text{Ave}\left(gr_t(n) - ew_t(n)\right)\right]]^{-1}$ and since k cancels out (see below) we leave it unspecified. This implies that log returns predicted by the model can be decomposed into:

$$\begin{aligned} p_t(n) - p_{t-1}(n) &\approx \rho\log\frac{EW_t(n)}{EW_{t-1}(n)} + (1-\rho)\log\frac{GR_t(n)}{GR_{t-1}(n)} \\ r_t(n) &= \rho r_t^e t(n) + (1-\rho)r_t^g(n) + \delta_t(n) \qquad (11) \\ r_t^e t(n) &\equiv ew_t(n) - ew_{t-1}(n) \\ r_t^g(n) &\equiv gr_t(n) - gr_{t-1}(n) \end{aligned}$$

where $\delta_t(n)$ represents an approximation error. This means that $\delta_t(n)$ does *not* necessarily have the properties of regression residuals, i.e. being orthogonal to the regressors. Nevertheless, the above equation suggests the following regression equation:

$$r_t(n) = \beta_0 + \beta_1 r_t^e t(n) + \beta_2 r_t^g(n) + \varepsilon_t(n) \tag{12}$$

and it is of interest to examine the sign and magnitude of the parameters β_1 and β_2, as well as the return profiles of $r_t^e t(n)$ and $r_t^g(n)$ separately. In an economy with negligible granularity effects, we expect β_2 and $r_t^g(n)$ to be small and insignificant. In contrast, in an economy where granularity plays a key role we are interested in the sign and magnitude of β_2 and $r_t^g(n)$. If the former is negative and the latter positive, then we can say that granularity results in a drag on expected returns. The opposite sign for β_2 would indicate a boost to returns.

Following the analysis in section C we will actually proceed with a decomposition involving the top players, namely as in equation (10) we can write:

$$\begin{aligned} P_t(n) &= \frac{1}{IS(n)} \sum_{i=1}^{I} \mathbf{A}_{i,t} + \\ & \frac{1}{S(n)} \sum_{i \in Top-k} \mathbf{A}_{i,t}(\frac{1}{I} - w_{i,t}(n)) + \frac{1}{S(n)} \sum_{i \notin Top-k} \mathbf{A}_{i,t}(\frac{1}{I} - w_{i,t}(n)) \end{aligned} \tag{13}$$

and therefore using similar notation as before:

$$\begin{aligned} \log P_t(n) = p_t(n) &= ew_t(n) + \log\left[1 + \frac{GR_t(n)^{Top-k} + GR_t(n)^{NoTop-k}}{EW_t(n)}\right] \\ &\approx k + \rho ew_t(n) + (1-\rho) gr_t(n)^{Top-k} + (1-\rho) gr_t(n)^{NoTop-k} \end{aligned}$$

which leads to the following regression model similar to (12):

$$r_t(n) = \beta_0 + \beta_1 r_t^e t(n) + \beta_2 r_t^g(n)^{Top-k} + \beta_3 r_t^g(n)^{NoTop-k} + \varepsilon_t(n) \tag{14}$$

Hence, in the above equation we have two granularity residuals, the first attributed to the top k players and the second pertaining to the remaining ones. Before we exploit the decompositions empirically, we need to explore the model specification in light of the potential impact of HHI on asset demand, which are the drivers of the components in equations (12) and (14).

3.2 A Specification Test

Koijen and Yogo (2019) consider a K-dimensional vector $\mathbf{x}_t(n)$ of observed characteristics of asset n at date t, which in their empirical work includes log book equity, profitability, investment, and market beta. Suppose now that there are characteristics which we like to consider, like say HHI, in addition to those already included in the original KY specification (see equation (A.2) in the Online Appendix). We collect these additional determinants of asset demand schemes in a vector $\mathbf{x}_t^A(n)$, where the superscript refers to the additional set being considered containing characteristics $K+1$ through K^A. A specification test regarding the inclusion of $\mathbf{x}_t^A(n)$ for stock n has the following null model:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) = \exp\left[\beta_{0,i,t} me_t(n) + \sum_{i=1}^{K-1} \beta_{k,i,t} x_{k,t}(n) + \beta_{K,i,t}\right] \varepsilon_{i,t}(n) \tag{15}$$

and alternative $H_A : \beta^A_{k,i,t} \neq 0$ for at least one k, i, t :

$$\begin{aligned} \frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) \quad &= \quad \exp\left[\beta_{0,i,t} me_t(n) + \sum_{i=1}^{K-1} \beta_{k,i,t} x_{k,t}(n) + \beta_{K,i,t}\right] \times \\ & \qquad \exp\left[\sum_{i=K+1}^{K^A} \beta^A_{k,i,t} x^A_{k,t}(n)\right] \tilde{\varepsilon}_{i,t}(n) \end{aligned}$$

In the above we separate the specification considered by Koijen and Yogo (2019) under the null and those under consideration in this paper under the alternative. For our analysis we focus on granularity and therefore:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) = \exp\left[\beta_{0,i,t} me_t(n) + \sum_{i=1}^{K-1} \beta_{k,i,t} x_{k,t}(n) + \beta_{K,i,t}\right] \times \exp\left[\beta^A_{K+1,i,t} HHI_{t-1}(n)\right] \tilde{\varepsilon}_{i,t}(n)$$

A LM-type testing approach is the following: we estimate the original model of Koijen and Yogo (2019), recover the demand shocks $\varepsilon_{i,t}(n)$ and run the regressions:

$$\log\left(\varepsilon_{i,t}(n)\right) = \alpha_{i,0} + \beta_{K+1,i,t} HHI_{t-1}(n) + \tilde{e}_{i,t}(n) \tag{16}$$

where $\tilde{e}_{i,t}(n) = \log \tilde{\varepsilon}_{i,t}(n)$. Note that the above approach has the advantage that we can use the estimation results from the Koijen and Yogo (2019) paper (although we reestimated their empirical model with a slightly longer data span ending in 2019Q1) and easily perform our test with the new candidate demand determinants, in our case lagged HHI. The advantage is that we do not start with a proliferation of characteristics which might cause multi-colinearity issues (as reported by Koijen and Yogo (2019)).

It is worth reminding ourselves that if we accept the null hypothesis, that means there is no impact of institutional investor concentration on demand-driven asset pricing, or at least any impact is absorbed by the characteristics already considered by Koijen and Yogo (2019). Conversely, if we reject the null either for all assets $n = 1, \ldots, N_t$, or for a subclass of assets, that could potentially have significant impact on some of the empirical findings of Koijen and Yogo (2019).

Figure 7 displays the regression coefficients of the Koijen and Yogo (2019) model latent demands on lagged HHI, estimated by-investor-type/by-quarter, with (point-wise) 95% confidence intervals per-quarter. The investor types are households (similar to Koijen and Yogo (2019) we treat households as the residual holders of equity not covered by institutional holdings), banks, insurance companies, investment advisors, mutual funds and pension funds. In the beginning of the sample there is evidence in favor of the null that granularity has no impact on investor demands, but in particular since the turn of the century there are clear indications across all investor types that HHI matters as a characteristic.

In Table 9 we report p-values for the LM specification tests regarding the average $\beta^A_{k,i,t}$ coefficients being zero in regression (16) across all assets and a given group of institutional investors being zero respectively over the full and post-1999 samples. As we can see from the table, there is again strong evidence certainly post-1999 that HHI affects investor's asset demands. For the full sample there is somewhat weaker evidence, particularly for mutual funds and pension funds.

Table 9: LM Specification Tests Granularity

	Full Sample	Post-1999
Panel A: Investor Type		
Banks	0.000	0.000
Insurance	0.000	0.000
Investor Advisors	0.087	0.000
Mutual Funds	0.551	0.000
Pension Funds	0.118	0.000
Households	0.029	0.035
Panel B: Top-10 Investors		
Top-10 Investors	0.000	0.000
Other Investors	0.000	0.000

Notes: This table shows p-values for LM specification tests regarding the average $\beta^A_{k,i,t}$ coefficients being zero in regression (16) across all assets and a given group of institutional investors being zero respectively over the full and post-1999 samples. In *Panel A* investors are segmented according to their type, and in *Panel B* they are segemented according to whether or not they are in the Top-10 of investors ranked by AUM.

3.3 New Model Specification - Variance Decomposition

It is clear from the analysis in the previous subsection that we need to re-estimate the KY model with lagged HHI as a characteristic. The starting point is the identifying assumption pertaining to the demand shocks appearing in equation (15), namely:

$$\mathbb{E}\left[\varepsilon_{it}(n) | me_t(n), x_t(n)\right] = 1 \tag{17}$$

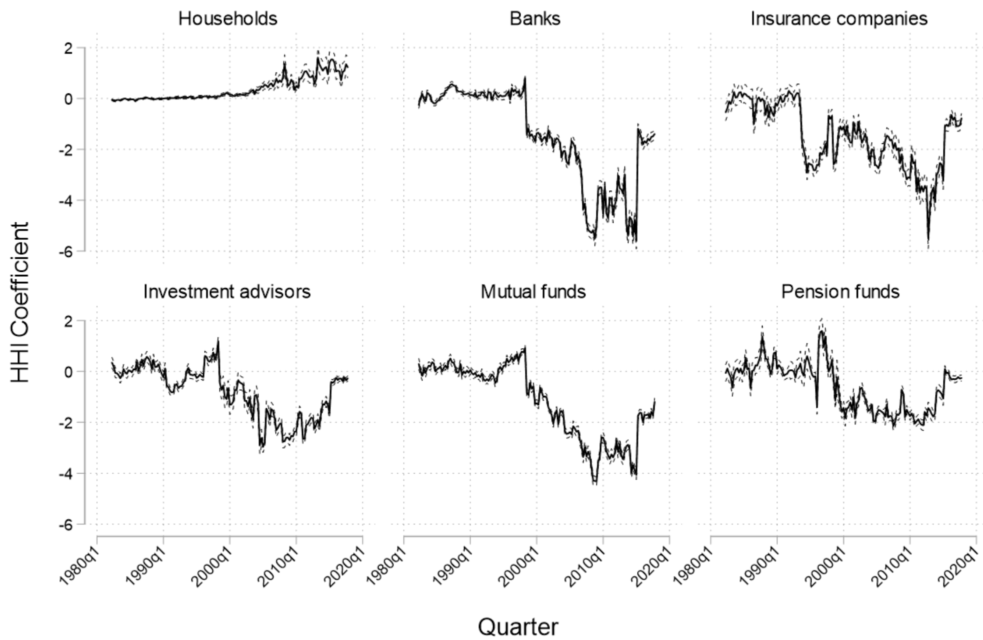


Fig. 7: Latent Demands on Lagged HHI Coefficients - AUM weighted/By Investor Type

where $me_t(n)$ is the log of market equity at time t, and $x_t(n)$ is a vector of observed characteristics of asset n at time t, which in our case includes lagged granularity measures as in equation (16). Let $\mathtt{1}_{it}(n)$ be an indicator function that is equal to one if asset n is in investor i's investment universe (i.e., $n \in \mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$). The choice of instruments in Koijen and Yogo (2019) is determined by $\mathtt{1}_{it}(n)$ being exogenous under the maintained assumption that the investment universe is exogenous, while $\varepsilon_{it}(n)$ is endogenous through the portfolio-choice problem. For each investor i let $\mathbf{A}_{i,t}$ be the wealth allocated at date t across assets in its investment universe $\mathcal{N}_{i,t}$ and an outside asset. In estimating investor i's asset demand, the instrument for log market equity of asset n is

$$\widehat{me}_{it}(n) = \log\left(\sum_{j \neq i} \mathbf{A}_{j,t} \frac{\mathtt{1}_{jt}(n)}{1 + \sum_{i=1}^{N} \mathtt{1}_{it}(n)}\right) \tag{18}$$

This instrument depends only on the investment universe of other investors and the wealth distribution, which are exogenous under our identifying assumptions. Hence, identification comes from cross-sectional variation in the investment universe and not from time-series variation in assets moving in and out of the investment universe. As noted by Koijen and Yogo (2019), the instrument can be interpreted as the counterfactual market equity, at the market clearing price, if other investors were to hold an equal-weighted portfolio within their investment universe.[8]

We maintain the same set of instruments as in Koijen and Yogo (2019) for at least two reasons. First, the instrument exploits variation in the investment universe across investors which we assume to be orthogonal to the predetermined lagged $HHI_{t-1}(n)$. The second reason is that using the same set of instruments as in Koijen and Yogo (2019) allows for an easier comparison of our estimates with theirs.

$$\mathbb{E}\left[\varepsilon_{it}(n)|\widehat{me}_{it}(n), x_t(n)\right] = 1 \tag{19}$$

To appreciate the results of the original KY model versus the augmented model, we report the variance decomposition of stock returns reported in Table 10 for the same sample as in the KY paper, i.e. ending in 2017Q4. The left panel pertains to the original KY model and replicates Table 3 of Koijen and Yogo (2019). The right panel shows the results for our new specification. The remarkable observation is the share of stock characteristics, moving from 9.70 to 63.80 as a result of adding HHI as a characteristic. At the bottom of Table 10 we report the changes across the two specifications - showing a vast increase in the role of characteristics and a diminished role by total latent demand.

3.4 Empirical Analysis - Granularity Decomposition

Armed with this new specification we report the regression parameter estimates for the granularity regression in equation (12), imposing the restriction that the coefficients add

[8]Following Koijen and Yogo (2019), we measure the investment universe as stocks that are currently held or ever held in the previous eleven quarters. In constructing the instrument, we exclude the household sector and aggregate only over institutions with little variation in the investment universe, for whom at least 95 percent of stocks that are currently held were also held in the previous eleven quarters.

Table 10: Variance Decomposition of Stock Returns

	Without HHI		With HHI	
	% of Var	SE	% of Var	SE
Shares Outstanding	2.10	0.20	2.90	0.30
Stock Characteristics	9.70	0.30	63.80	7.40
Dividend Yield	0.40	0.00	0.40	0.00
AUM	2.30	0.10	2.70	0.10
Coefficients	4.70	0.20	-4.90	3.40
Latent Demand (extensive)	23.30	0.30	53.70	6.90
Latent Demand (intensive)	57.50	0.40	-18.30	5.00
Observations	134,328		134,137	
Total Latent Demand	80.80		35.40	
Change From Without HHI				
			Chg.	% Chg.
Characteristics			54.10	557.7%
Total Latent Demand			-45.40	-56.2%

Notes: This table shows results for the estimated regressions in equation (6). Quarterly sample starts in 1980Q1 and ends in 2017Q4. Newey and West (1987) standard errors are in column SE.

up to one. Most of our focus in this section will be on separating the top 10 institutional investors to sharpen our analysis, as we reported previously in this paper there is ample evidence to separate small from large institutions. Hence, our analysis uses the regression equation (14). Before doing so, we draw attention to Table 11 Panel A where we list the result for the sorted HHI portfolios from low to high. We continue with the sample ending in 2017Q4 as in the previous table. Although not monotone, we see that high HHI portfolio returns are more negatively affected by granular residuals. In terms of interpretation of the decomposition, recall that the increasing negative slope coefficients means that granularity results in a drag on expected returns as HHI increases (since the granularity residual mean return is positive and equal to 0.11 with a standard deviation of 0.90).

Figure 8 covers the interquartile range for High/Low HHI portfolios top 10 institutional investors, and Figure 9 pertains to downside risk again for the Top 10 investors.[9] Last but not least, in Table 11 Panel B we document parameter estimates for the top 10 versus other investors. In the Online Appendix F we provide supplementary results, including regression parameter estimates as well as plots for other institutional investor configurations.

From our previous analysis, we know that the variance of HHI-sorted portfolios increases with investor concentration. The plots in Figure 8 tells us that the granularity residuals of the top 10 investors are a major component of volatility of high HHI portfolios while all others contribute very little. In fact the granularity residual IQR for high HHI is *smaller* for all other investors (bottom right panel). The large bursts in volatility for equally and top 10 investors coincide, with the scale implying that 40 % of the volatility for high HHI portfolios is coming from the top 10 investor granular residuals. A similar pattern emerges for downside risk, as displayed in Figure 9. The granular residual component of the top 10 investors is the source of major downside risk. In contrast the equally weighted components are overall more stable.

Table 11 Panel B displays the regression parameter estimates for the granularity decom-

[9]The granularity decomposition for mean returns is less informative and appears in Online Appendix Figure F.7.

Table 11: Granularity Decomposition Regression Parameter Estimates By HHI Portfolio

Panel A

	Granularity Residual		Equal Weights	
	Est.	SE	Est.	SE
Low	-0.099	0.003	1.099	0.003
2	-0.090	0.005	1.090	0.005
3	-0.146	0.009	1.146	0.009
4	-0.262	0.035	1.262	0.035
High	-0.162	0.023	1.162	0.023

Panel B: Top 10 vs. Other Investors By HHI Portfolio

	Granularity Residual				Equal Weights	
	Top 10		Other Investors			
	Est.	SE	Est.	SE	Est.	SE
Low	0.169	0.004	0.216	0.003	0.615	0.005
2	0.063	0.003	0.197	0.005	0.740	0.005
3	-0.016	0.009	0.241	0.015	0.775	0.022
4	-0.309	0.119	0.167	0.070	1.142	0.178
High	-0.245	0.095	0.521	0.031	0.724	0.106

Notes: This table shows results for regressions in equations (12) – Panel A – and (14) – Panel B. Quarterly sample starts in 1982Q1 and ends in 2017Q4. Newey and West (1987) standard errors are in column SE.

position involving a separation of the top 10 investors. For the low HHI portfolio we note that the top 10 institutional investors, as well as the other investors, have a positive impact, compared to the negative slope in Panel A, the latter implying a negative impact of granular residuals on returns albeit small. Turning to the high HHI portfolios, we see a dramatic difference, however. Granular residuals play an important role – large and negative – for the top 10 investors.

4 Conclusion

The number, size, and influence of institutional investors has increased dramatically over the past thirty years. In order to study the impact that institutional investors may have on asset prices, we represent the composition and holdings of institutional investors through an investor granularity characteristic (HHI) at the asset level. Our analysis indicates that investor granularity is an important characteristic in the cross-section of asset returns. A self-financing trading strategy that goes long low HHI stocks and short high HHI stocks delivers an average return spread that is not fully explained by common financial or liquidity factors in an unconditional setting. Moreover stocks with a high investor concentration tend to exhibit conditional volatility and downside risk that is more susceptible to increases in that investor concentration.

Next we turned our attention to demand driven asset pricing models of the type proposed by Koijen and Yogo (2019) and showed that their original specification appears to be mis-specified with regards to impact of investor concentration on institutional asset demands. Correcting for this missing characteristic, we re-estimate the model and find that HHI plays an important role. To appreciate the results of the original KY model versus the augmented model, we report the variance decomposition of stock returns and find a vast increase in the role of characteristics and a diminished role by total latent demand.

Next, we introduce a decomposition of returns based on what we call granularity residuals

Fig. 8: Granularity decomposition: Interquantile Range High/Low HHI Portfolios Top 10

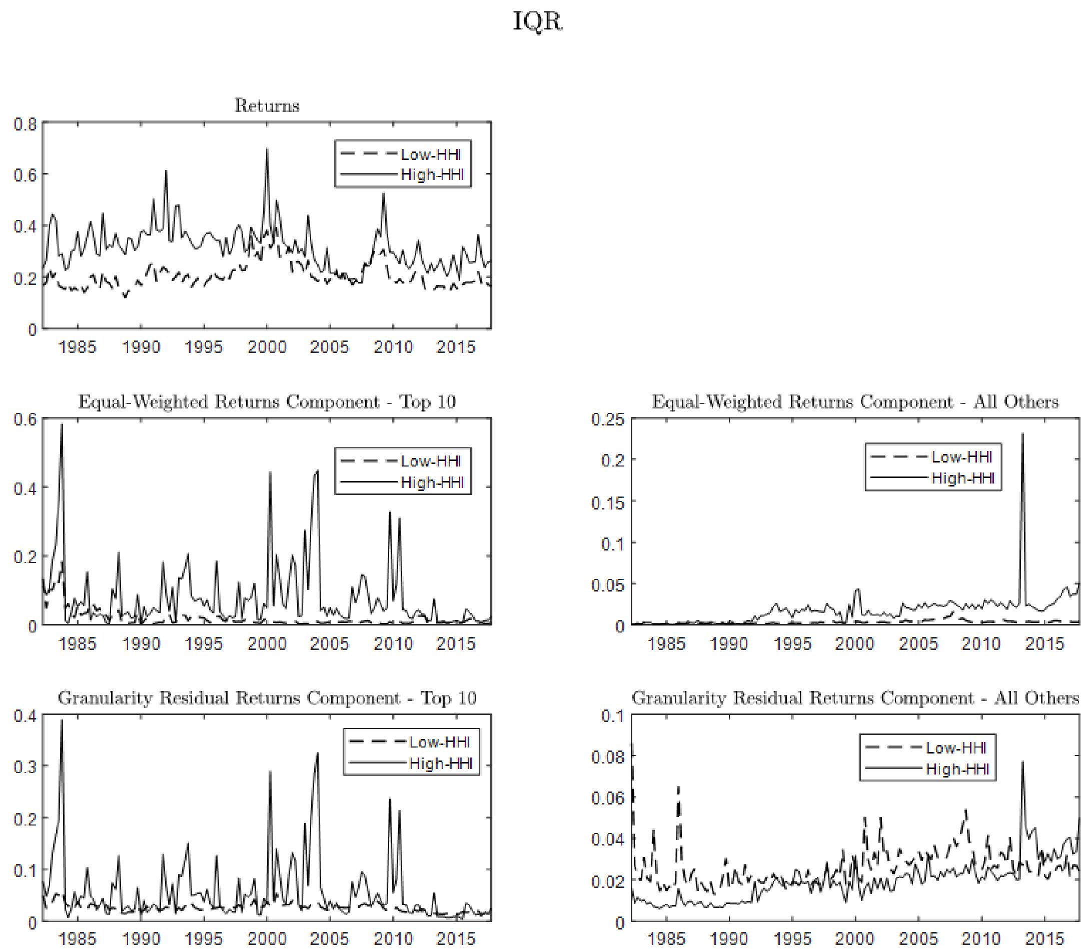
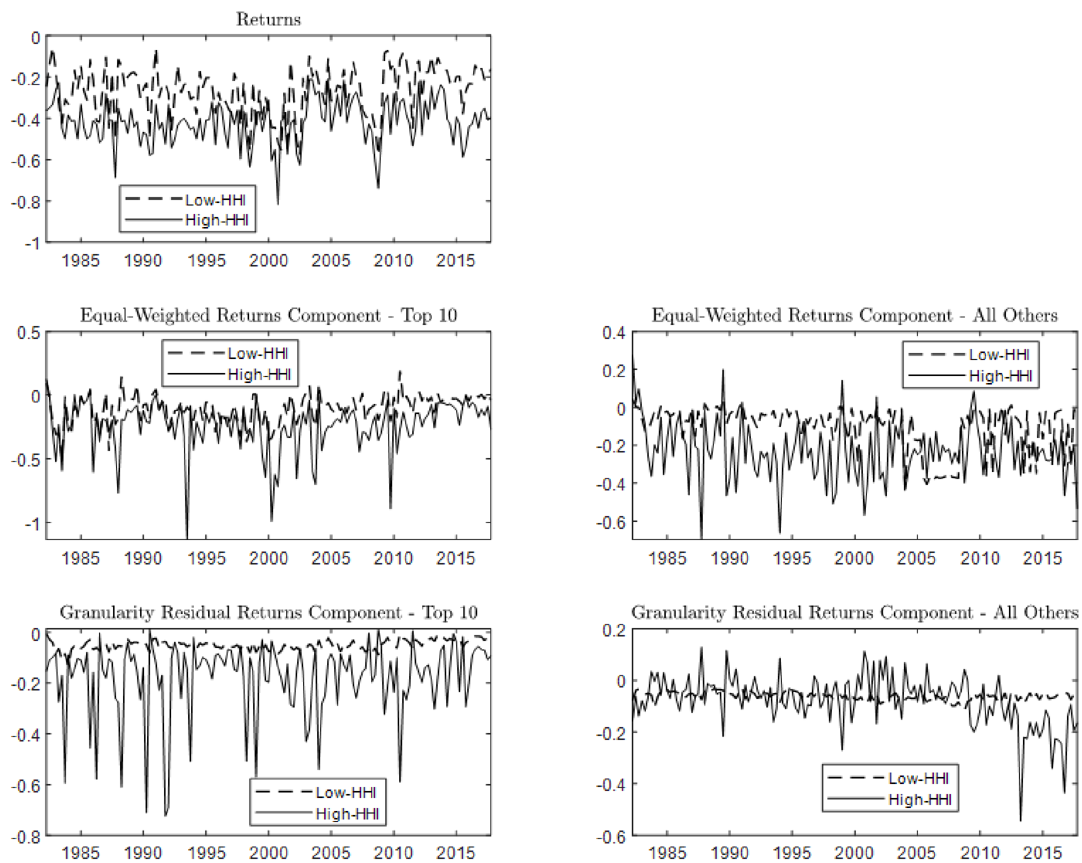


Fig. 9: Granularity decomposition: Downside Risk High/Low HHI Portfolios Top 10

5% Quantile



which allows us to better understand the impact of HHI on the pricing of equities. Armed with our new specification we report the regression parameter estimates for the decomposition. We find that the granularity residuals of the top 10 investors are a major component of volatility of high HHI portfolios while all others contribute very little. The large bursts in volatility for equally and top 10 investors coincide, with the scale implying that 40 % of the volatility for high HHI portfolios is coming from the top 10 investor granular residuals. A similar pattern emerges for downside risk. In terms of the regression parameter estimates for the granularity decomposition we note that the top 10 institutional investors, as well as the other investors, have a positive impact. Turning to the high HHI portfolios, we see a dramatic difference, however. Granular residuals play an important role – large and negative – for both the top 10 as well as the other investors.

The analysis in this paper prompts policy questions regarding the impact of large institutional investors. Stylized facts as well as granularity decompositions all point to a disproportionate impact of large institutional investors on volatility and downside risk.

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Online Appendix

A A Heterogeneous Investor Demand-driven Model

We adopt the framework in Koijen and Yogo (2019), hereafter (KY). In this section we provide a summary of their model.

Assets There are N financial assets indexed by $n = 1, \ldots, N$. Let $S_t(n)$ be the number of shares outstanding of asset n at date t. Let $P_t(n)$ and $D_t(n)$ be the price and dividend per share for asset n at date t. Then $ME_t(n) = P_t(n)S_t(n)$ is market equity at date t, and $R_t(n)$ is the gross return from date $t-1$ to t. Lowercase letters denote the logarithm of the corresponding uppercase variables. The N-dimensional vectors corresponding to these variables in bold as $\mathbf{s}_t = \log(\mathbf{S}_t)$, $p_t = \log(\mathbf{P}_t)$, and $\mathbf{r}_t = \log(\mathbf{R}_t)$. We denote a vector of ones as $\mathbf{1}$, a vector of zeros as $\mathbf{0}$, an identity matrix as $\mathbf{I}$, and a diagonal matrix as $\text{diag}(\cdot)$. In addition to price and shares outstanding, the assets are differentiated along K characteristics (the K^{th} being a constant). We denote characteristic k of asset n at date t as $x_{k,t}(n)$. We stack these characteristics in an $N \times K$ matrix as $\mathbf{x}_t$, whose n^{th} row is $\mathbf{x}_t(n)'$ and $(n,k)^{th}$ element is $x_{k,t}(n)$.

Investors The financial assets are held by I investors, indexed by $i = 1, \ldots, I$. Each investor i allocates wealth $\mathbf{A}_{i,t}$ at date t across assets in its investment universe $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$ and an outside asset. The investment universe is a subset of assets that the investor is allowed to hold, which in practice is determined by an investment mandate. For example, the investment universe of an index fund is the set of assets that compose the index. We denote the number of assets in the investment universe as $|\mathcal{N}_{i,t}|$. The outside asset represents all wealth outside the N assets. Let $w_{i,t}$ be an $|\mathcal{N}_{i,t}|$-dimensional vector of portfolio weights investor i chooses at date t. The investor chooses the portfolio weights at each date to maximize expected log utility over time T terminal wealth: $\max_{w_{i,t}} \mathbb{E}_{i,t}\left[\log\left(\mathbf{A}_{i,t}\right)\right]$ subject to the intertemporal budget constraint: $\mathbf{A}_{i,t+1} = \mathbf{A}_{i,t}[R_{t+1}(0) + \mathbf{w}'_{i,t}(\mathbf{R}_{t+1} - R_{t+1}(0)\mathbf{1})]$ in addition to short-sale constraints $\mathbf{w}_{i,t} \geq 0$, $\mathbf{1}'\mathbf{w}_{i,t} < 1$, and with $R_{t+1}(0)$ the gross return on the outside asset, $\mathbb{E}_{i,t}$, the expectation operator for investor i at time t. Lemma 1 of KY states that the first-order condition for the portfolio-choice problem is:

$$\mathbb{E}_{i,t}\left[\left(\frac{\mathbf{A}_{i,t+1}}{\mathbf{A}_{i,t}}\right)^{-1}\mathbf{R}_{t+1}\right] = \mathbf{1} - (\mathbf{I} - \mathbf{w}'_{i,t}\mathbf{1})(\Lambda_{i,t} - \lambda_{i,t}\mathbf{1}) \tag{A.1}$$

where $\Lambda_{i,t}$ and $\lambda_{i,t}$ are the Lagrangian multipliers of the short-sale constraints.

Characteristics-Based Demand Consider $\mathbf{x}_t(n)$ the vector of observed characteristics of asset n at date t, which in the empirical work of KY includes log book equity, profitability, investment, and market beta. Under heterogeneous beliefs, different investors could form different expectations about returns based on the same observed characteristics. Moreover, investor i forms expectations based on the information set:

$$\hat{\mathbf{x}}_{i,t}(n) = \begin{bmatrix} me_t(n) \\ \mathbf{x}_t(n) \\ \log\left(\varepsilon_{i,t}(n)\right) \end{bmatrix}$$

which consists of log market equity, other observed characteristics, and unobserved characteristics. Let $\mu_{i,t}(n)$ be the investor i expected return for asset n and time t and $\Sigma_{i,t}$ the conditional covariance matrix across assets. A key Assumption 1 in KY states the following:

Assumption A.1. *Expected excess returns and factor loadings are polynomial functions of characteristics:*

$$\begin{aligned} \mu_{i,t}(n) &= \mathbf{y}'_{i,t}\Phi_{i,t} + \phi_{i,t} \\ \Gamma_{i,t}(n) &= \mathbf{y}'_{i,t}\Psi_{i,t} + \psi_{i,t} \\ \Sigma_{i,t} &= \Gamma_{i,t}(n)\Gamma_{i,t}(n)' + \gamma_{i,t}\mathbf{I} \end{aligned}$$

where $\Gamma_{i,t}(n)$ is a vector of factor loadings, $\gamma_{i,t}(n) > 0$ is idiosyncratic volatility and where $\Phi_{i,t}$ and $\Psi_{i,t}$ are vectors and $\phi_{i,t}$ and $\psi_{i,t}$ are scalars that are constant across assets.

The vector $\mathbf{y}_{i,t}$ is M^{th}-order polynomial of $\hat{\mathbf{x}}_{i,t}(n)$ (see KY for details). As a result, an asset's own characteristics are sufficient for its factor loadings in the conditional mean and variance, which also implies that they are sufficient for the variance of the optimal portfolio. Corollary 1 of KY then states that a restricted version of the optimal portfolio under Assumption 1 is characteristics-based demand:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) = \exp\left[\beta_{0,i,t} me_t(n) + \sum_{i=1}^{K-1} \beta_{k,i,t} x_{k,t}(n) + \beta_{K,i,t}\right] \varepsilon_{i,t}(n) \tag{A.2}$$

Assumption 2 of KY imposes the restriction that $\beta_{0,i,t}$, namely:

Assumption A.2. *The following holds for all investors: $\epsilon_{i,t}(n) \geq 0$, and $\beta_{0,i,t} < 1$, $\forall i$*

The above equation and the budget constraint imply that investor i's portfolio weight on asset any $n \in \mathcal{N}_{i,t}$ and the outside asset at date t is

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)} \qquad w_{i,t}(0) = \frac{1}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)} \tag{A.3}$$

Demand Elasticities Investors have heterogeneous demand elasticities. To characterize these, let $q_{i,t} = \log(\mathbf{A}_{i,t} w_{i,t})$ - p_t be the vector of log shares held by investor i, defined only over the subvector of strictly positive portfolio weights. The elasticities of respectively individual demand and aggregate demand are:

$$\begin{aligned} -\frac{\partial q_{i,t}}{\partial p_t'} &= \mathbf{I} - \beta_{0,i,t}\text{diag}(\mathbf{w}_{i,t})'\mathbf{G}_{i,t} \\ -\frac{\partial q_t}{\partial p_t'} &= \mathbf{I} - \sum_{i=1}^{I} \beta_{0,i,t}\mathbf{A}_{i,t}\mathbf{H}^{-1}\mathbf{G}_{i,t} \end{aligned}$$

where $\mathbf{G}_{i,t} = \text{diag}(\mathbf{w}_{i,t})$ - $\mathbf{w}_{i,t}\mathbf{w}_{i,t}'$, $q_t = \log(\sum_{i=1}^{I} \mathbf{A}_{i,t} w_{i,t})$ - p_t be the vector of log shares held across all investors, summed only over the subvectors of strictly positive portfolio weights, and finally $\mathbf{H} = \sum_{i=1}^{I} \mathbf{A}_{i,t}\text{diag}(\mathbf{w}_{i,t})$.

Market Clearing For each asset n we have that $\text{ME}_t(n) = \sum_{i=1}^{I} \mathbf{A}_{i,t} w_{i,t}(n)$ which can be rewritten in log and vector notation as:

$$\mathbf{p} = f(\mathbf{p}) = \log\left[\sum_{i=1}^{I} \mathbf{A}_i \mathbf{w}(\mathbf{p})\right] - \mathbf{s} \tag{A.4}$$

Proposition 2 of KY states that $f(\mathbf{p})$ has under suitable regularity conditions a unique fixed point which provides the solution to the market clearing price.

B HHI Portfolio Analysis Details

We use institutional 13-F filings from the Thomson-Reuters Institutional Holdings Database. This database provides ownership information of institutional investment managers with assets under management of over \$100 million in Section 13(f) securities.

Figure B.1 reports the number of institutional investors for our sample from 1980Q1 to 2019Q1. We note that the number increases to 4420 in 2019Q1. The plot reaches its peak of 4686 institutions in 2017Q4. During the 2008 financial crisis, there has been a decrease in the number of 13-F institutions.

With respect to the aggregate dollar holdings appearing in Figure B.2, we observe several substantial drops in the early 2000s. Quite naturally, this was the case during the global financial crisis as well. In spite of these instances, the dollar amount held by the 13-F institutions increased from \$321 billion in 1980Q1 to \$21 trillion in 2019Q1.

B.1 Portfolio Construction

The cross-section of stocks is sortable by ownership concentration H_t^e defined in equation (2) in the paper. The portfolio formulation strategy is implemented as follows:

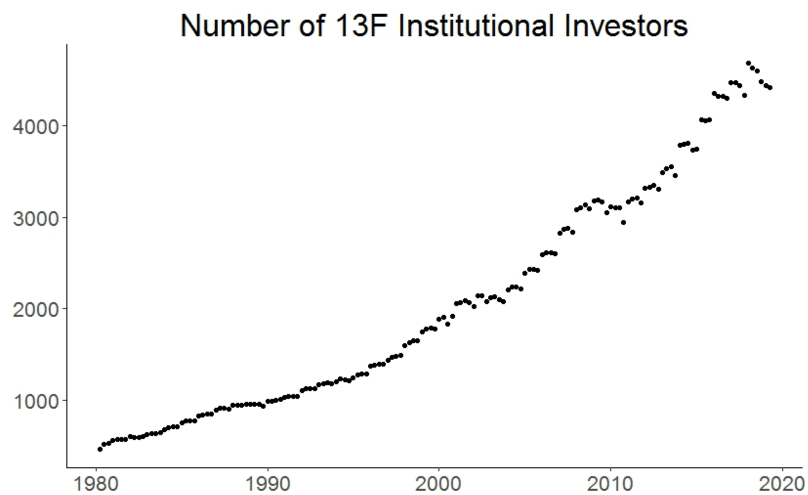


Fig. B.1: Quarterly Number of Institutional Investors

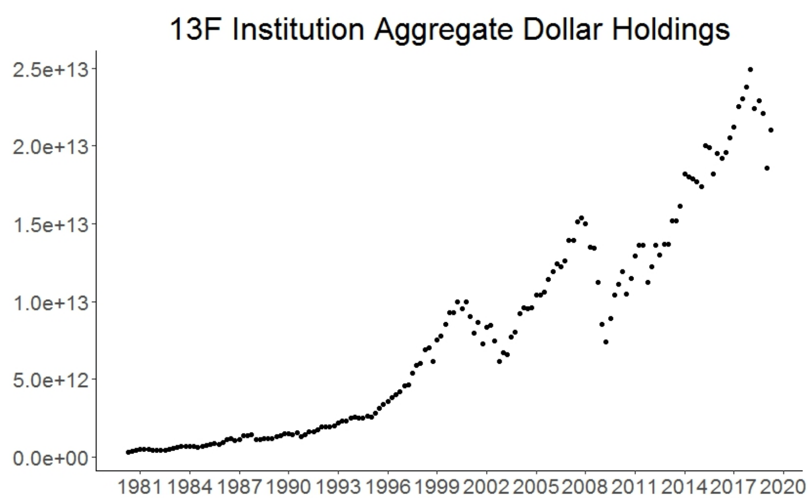


Fig. B.2: Quarterly Institutional Investment Manager Holdings

(1) sort the securities by HHI in descending order,

(2) find the quintile cutoffs of HHI and correspondingly divide the securities into 5 portfolios,

(3) in a case where more than 20% of the securities have HHI = 1

- adjust by letting HHI* = HHI - e, where e $\sim$ Uniform(0, c),

- c is defined as the difference between 1 and the next largest HHI value.

The 5 portfolios are rebalanced annually. We base the portfolio cutoffs on first quarter HHI values, thus avoid omitting the securities that enter the filings mid-year. We present the

Table B.1: Portfolio HHI Summary Statistics

Portfolio	1	2	3	4	5
Mean	0.9617	0.6228	0.2830	0.1241	0.0465
Median	1	0.6699	0.2748	0.1171	0.0471
Std. Dev.	0.0510	0.1512	0.0535	0.0261	0.0067

Notes: This table shows descriptive statistics of HHI by portfolio. Portfolio 1 has the highest average HHI and consists of stocks only held by a few institutions, whereas portfolio 5 has the lowest average HHI and includes stocks with a wide owner base. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

HHI compositions for each portfolio in Table B.1. Portfolio 1 has the highest HHI overall, and typically consists of niche stocks with a sole holder. Portfolio 5, on the other hand, is mainly comprised of large-cap stocks that are traded extensively.

B.2 HHI Decomposition

We decompose the portfolio HHI into a portion that can be attributed to the top 3/5/10 institutions and the rest of the shares. The mean values for this decomposition is presented in Table B.2. The relationship HHI = HHI(k) + HHI(-k) holds for k = 3, 5, and 10. On average, the largest institutions contribute more to the concentration in low-HHI portfolios.

The descriptive statistics of the 5 HHI portfolios are summarized in Table B.3 - recall that portfolio 1 is high-HHI, held by a single institutional investor, portfolio 5 is low-HHI comprising of stocks held by many.

B.3 Low-Minus-High (LMH) Portfolio Characteristics

The excess returns are presented in annualized percentages. The descriptive statistics of the low minus high (LMH) HHI portfolios are summarized Table B.3. These are portfolios that

Table B.2: Portfolio HHI Decomposition

Portfolio	1	2	3	4	5
Mean	0.9617	0.6228	0.2830	0.1241	0.0465
HHI(3)	0.0403	0.0307	0.0193	0.0117	0.0067
HHI(-3)	0.9214	0.5921	0.2637	0.1125	0.0399
HHI(5)	0.0492	0.0373	0.0246	0.0153	0.0090
HHI(-5)	0.9125	0.5855	0.2584	0.1088	0.0375
HHI(10)	0.0818	0.0567	0.0377	0.0229	0.0128
HHI(-10)	0.8799	0.5661	0.2453	0.1012	0.0337

Notes: This table shows portfolio averages of HHI, HHI(k), and HHI(-k) for k = 3, 5, and 10. The expression HHI(k) represents concentration attributed to top-k institution holdings, and HHI(-k) represents concentration resulting from holdings of all other institutional investors. Portfolio HHI is the sum of these two terms. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

are long in high ownership breadth stocks and short stocks held by few institutional investors. The excess returns are presented in annualized percentages. The LMH portfolios delivers on average a 5.6% annualized excess return, significantly different than 0 at the 1% level. In addition, the portfolio mean returns display a monotonically increasing return pattern, and we reject the null of no monotonically increasing pattern (p-value of 1.5%) using the monotonicity test of Patton and Timmermann (2010). It is also interesting that there is a monotonically decreasing pattern in the *higher* moments of the returns. Volatility, skewness, and kurtosis are all monotonically *decreasing* from high-HHI to low-HHI portfolios.

Table B.3: Annualized Portfolio Returns

Portfolio	1	2	3	4	5	Low-High (LMH)
Mean	-2.5029	-2.3392	-1.3113	0.3528	3.0709	5.5738
Median	-2.4784	-1.6840	-1.0845	1.1456	4.6916	7.7628
Std. Dev.	12.6901	8.1875	8.0360	8.0076	7.0789	11.0350
Skewness	2.8848	-0.5091	-0.5142	-0.5311	-0.6122	-5.9918
Kurtosis	24.7858	4.2225	4.1688	4.1508	3.7752	57.3298
25% Perc.	-16.0652	-11.1071	-10.4773	-8.5039	-5.5814	-0.7477
75% Perc.	7.8166	7.6248	8.2365	10.9354	11.9620	14.2492

Notes: This table shows descriptive statistics of annualized portfolio returns in percentages. We report values for the 5 HHI portfolios as well as the Low-Minus-High (LMH) portfolio. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

We also calculate a liquidity-risk adjusted excess return ($\alpha_i + \epsilon_{i,t}$) extracted from:

$$R_{i,t} = \alpha_i + \beta_i \times liq_t + \epsilon_{i,t}.$$

The results appear in the Table B.4. The LMH portfolio returns like quite similar to those reported in Table B.3.

Table B.4: Liquidity-Risk Adjusted Excess Returns

Portfolio	1	2	3	4	5	Low-High (LMH)
Mean	-2.9739	-2.3017	-1.1975	0.5299	3.2579	6.2318
Median	-3.9177	-1.6299	-0.9180	1.2071	4.8309	8.1603
Std. Dev.	12.6064	8.1577	8.0035	7.9703	7.0427	10.9098

Notes: This table shows descriptive statistics of annualized liquidity-adjusted portfolio returns in percentages. We report values for the 5 HHI portfolios as well as the Low-Minus-High (LMH) portfolio. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

B.4 Equally-Weighted Linear Factor Model Details

In Table B.5 we report conditional mean linear factor model estimates using the Fama-French 3-factor model (FF3), the same model augmented with the liquidity factor and finally augmented with both liquidity and HHI.

Table B.5: Conditional Mean Linear Factor Models

	Rm-Rf		SMB		HML		LIQ		PC-HHI
	FF3 - GMM J-stat p-val 0.00								
Betas									
1 (High HHI)	0.220	***	0.460	***	0.189	*			
	(0.076)		(0.106)		(0.109)				
2	0.298	***	0.324	***	0.057	***			
	(0.023)		(0.047)		(0.019)				
3	0.321	***	0.314	***	0.055	***			
	(0.018)		(0.040)		(0.016)				
4	0.349	***	0.307	***	0.064	***			
	(0.012)		(0.027)		(0.009)				
5 (Low HHI)	0.343	***	0.204	***	0.038	***			
	(0.006)		(0.013)		(0.012)				
Price of Risk	0.070	**	-0.107	*	0.145				
	(0.029)		(0.062)		(0.114)				
	FF3+Liquidity - GMM J-stat p-val 0.00								
Betas									
1 (High HHI)	0.226	***	0.459	***	0.190	*	0.113		
	(0.086)		(0.127)		(0.108)		(0.129)		
2	0.280	***	0.371	***	0.048	**	0.018		
	(0.022)		(0.056)		(0.022)		(0.029)		
3	0.314	***	0.335	***	0.052	***	0.013		
	(0.016)		(0.044)		(0.015)		(0.024)		
4	0.366	***	0.273	***	0.072	***	0.012		
	(0.012)		(0.025)		(0.011)		(0.013)		
5 (Low HHI)	0.363	***	0.155	***	0.047	***	0.012	*	
	(0.006)		(0.013)		(0.011)		(0.007)		
Price of Risk	0.044	***	-0.049	**	-0.046	**	0.134		
	(0.011)		(0.024)		(0.021)		(0.085)		
	FF3+Liquidity+HHI - GMM J-stat p-val 0.00								
Betas									
1 (High HHI)	0.214	**	0.488	***	0.185	**	0.104		0.001
	(0.095)		(0.157)		(0.091)		(0.124)		(0.019)
2	0.298	***	0.326	***	0.053	**	0.035		-0.002
	(0.021)		(0.053)		(0.025)		(0.037)		(0.011)
3	0.329	***	0.303	***	0.056	***	0.021		0.004
	(0.016)		(0.044)		(0.017)		(0.030)		(0.008)
4	0.363	***	0.276	***	0.072	***	0.011		-0.004
	(0.012)		(0.024)		(0.011)		(0.015)		(0.005)
5 (Low HHI)	0.355	***	0.176	***	0.046	***	0.004		-0.002
	(0.006)		(0.014)		(0.011)		(0.007)		(0.003)
Price of Risk	0.056	***	-0.082	**	0.050		0.104	*	0.206
	(0.014)		(0.041)		(0.061)		(0.062)		(0.236)

Notes: This table shows GMM estimation results for the system in equation (**??**) in the paper. Quarterly sample starts in 1980Q1 and ends in 2014Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

C Downside Risk and Top Players

In this section, we will examine the impact of top-3, top-5, and top-10 institutional investors. We noted in the main body of the paper that these groups of institutional investors are heterogeneous throughout our sample, as none has appeared consistently as a top player.

C.1 Firm-Level Downside Risk by Top Players

We investigate downside risk also through the analysis of firm-level fixed effects regressions of various risk measures on the decomposition of HHI. This is similar to the analysis done by Ben-David, Franzoni, Moussawi, and Sedunov (2016) who analyze firm conditional volatility in a panel data setting, but we focus exclusively on a broader set of downside risk measures. We first decompose each HHI measure for the firm into HHI attributed to the top 3 investors ($HHI(3)$) and total HHI less the HHI attributed to the top 3 investors ($HHI(-3)$). At the firm level we construct a variety of quarterly risk measures: realized quantiles (1% and 5% levels), downside variance, and risk-neutral variance estimates - where the latter is discussed in the next subsection. Given our reliance on options data discussed in the next subsection, our sample period for all risk measures is from 1996Q1-2013Q4. Downside variance for a given period t is defined as $DR_{i,t} = \sum_{j=1}^{T_t} r_{i,j}^2 1(r_{i,j} < 0)$ given daily returns for stock i on day j.

Once we compute the set of quarterly risk measures at the firm level, we estimate the following regression with both firm– and time– fixed effects (respectively FE_i and TE_t) in order to analyze the impact of investor concentration from the top 3 investors.

$$\begin{aligned} Risk_{i,t} = \beta_{i,0} + \beta_{i,1} Risk_{i,t-1} + \beta_{i,2} HHI(3)_{i,t-1} + \beta_{i,3} HHI(-3)_{i,t-1} \\ + \beta_{i,4} \ln(MrktCap)_{i,t-1} + \beta_{i,5} BM_{i,t-1} + FE_i + TE_t + \epsilon_{i,t} \end{aligned} \tag{C.1}$$

We present results in Table C.1 Panel A. We find that an increase in investor concentration for the top 3 investors is associated with a statistically significant increase in conditional risk across all of our risk measures. Investor concentration excluding the top 3 investors is also associated with a statistically significant - but substantially smaller compared to the top 3 - increase in risk, except for the risk-neutral variance measure. For the latter the impact is only significant for the top 3, but not for the remaining institutions. Finally, while the book-to-market ratio of a firm is not significantly associated with conditional risk, we do find that larger cap companies display lower conditional risk on average.

We also compute the quarterly risk measures using monthly risk measures for months January, April, July, and October to correspond to calendar quarters ending in March, June, September, and December respectively. This is done as a robustness check on whether the impact of investor concentration on conditional risk is immediate and transient during a quarter. We find that our results (Table C.1 Panel B) are similar whether we use quarterly conditional risk measures constructed using only data from the first month of the quarter or data from the entire three months of the quarter.

We also look at this model but using HHI decomposed into the top 5 and the top 10 investors. Notably we find that our results become statistically insignificant when we expand the top investor universe. This reinforces the idea that increasing investor concentration is especially impactful on risk when concentrated into the top influential investors.

C.2 Top Players - Dynamic Specifications

We also consider another set of dynamic models, namely the following specifications:

$$
\begin{aligned}
q_{i,t}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI_{i,t-1} + v_{i,t} \qquad \text{(C.2)} \\
q_{i,t}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI_{i,t-1} + b_{i,3}Liq_{t-1} + v_{i,t} \\
q_{i,t}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i,t-1} + b_{i,2}HHI_{i,t-1} + b_{i,3}Liq_{t-1} + b_{i,4}SMB_{t-1} + v_{i,t}
\end{aligned}
$$

Table C.1: Firm-Level Risk on Investor Concentration Regressions

	$Risk_{i,t}$ Measure			
	$RQ(0.05)_{i,t}$	$RQ(0.01)_{i,t}$	$DownVar_{i,t}$	$RN-Var_{i,t}$
	Panel A: Full Quarter			
$Risk_{i,t-1}$	0.0539***	0.0165***	0.0445***	0.0144**
	(0.0085)	(0.0064)	(0.0093)	(0.0072)
$HHI(3)_{i,t-1}$	−0.0649***	−0.0949***	0.0042***	0.4846***
	(0.0136)	(0.0263)	(0.0009)	(0.1062)
$HHI(-3)_{i,t-1}$	−0.0124***	−0.0163**	0.0008***	0.0339
	(0.0041)	(0.0080)	(0.0002)	(0.0421)
$\ln(MrktCap)_{i,t-1}$	0.0035***	0.0058***	−0.0002***	−0.0570***
	(0.0005)	(0.0010)	(0.0000)	(0.0063)
$BM_{i,t-1}$	−0.0014	−0.0026	0.0001	0.0030
	(0.0014)	(0.0024)	(0.0001)	(0.0192)
	Panel B: 1st Month of Quarter			
$Risk_{i,t-1}$	0.3968***	0.3066***	0.3520***	0.2840***
	(0.0122)	(0.0118)	(0.0221)	(0.0165)
$HHI(3)_{i,t-1}$	−0.0326***	−0.0495**	0.0024***	0.3965***
	(0.0094)	(0.0215)	(0.0009)	(0.1003)
$HHI(-3)_{i,t-1}$	−0.0086**	−0.0074	0.0003	0.1124***
	(0.0038)	(0.0086)	(0.0003)	(0.0414)
$\ln(MrktCap)_{i,t-1}$	0.0010***	0.0019**	0.0000	−0.0459***
	(0.0003)	(0.0008)	(0.0000)	(0.0044)
$BM_{i,t-1}$	−0.0025***	−0.0034**	0.0002***	0.0402***
	(0.0007)	(0.0016)	(0.0001)	(0.0129)

Notes: This table shows results for the estimated regressions in equation (C.1). Quarterly sample starts in 1996Q1 and ends in 2013Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Newey and West (1987) standard errors appear in parentheses.

$$
\begin{aligned}
q_{i,t}(.05) &= b_{i,0} + b_{i,1} RQ(.05)_{i,t-1} + b_{i,2} HHI(k)_{i,t-1} + b_{i,3} HHI(-k)_{i,t-1} + v_{i,t} \quad \text{(C.3)} \\
q_{i,t}(.05) &= b_{i,0} + b_{i,1} RQ(.05)_{i,t-1} + b_{i,2} HHI(k)_{i,t-1} + b_{i,3} HHI(-k)_{i,t-1} \\
&+ b_{i,4} Liq_{t-1} + v_{i,t} \\
q_{i,t}(.05) &= b_{i,0} + b_{i,1} RQ(.05)_{i,t-1} + b_{i,2} HHI(k)_{i,t-1} + b_{i,3} HHI(-k)_{i,t-1} \\
&+ b_{i,4} Liq_{t-1} + b_{i,5} SMB_{t-1} + v_{i,t}
\end{aligned}
$$

where k = 3, 5, 10. Aside from HHI and the other control variables, we add 5% realized quantiles of the return series to the equations. We use realized quantiles - as this will also be the model used for the individual firm panel regressions. Estimating dynamic panel quantile regressions is a daunting task, whereas using lagged realized quantiles significantly simplify the estimation procedures involved.

Table C.2: Regression of Conditional Quantile on HHI - Quarterly

	Constant		RQ	HHI		LIQ	SMB	R^2
High HHI	0.0028		-0.0060	-0.0962	***			0.3489
	(0.0088)		(0.1294)	(0.0083)				
Low HHI	-0.0412	***	-0.0640	-0.1181	***			0.0411
	(0.0050)		(0.0953)	(0.0347)				
High HHI	0.0031		0.0011	-0.0956	***	-0.0219		0.3507
	(0.0088)		(0.1297)	(0.0083)		(0.0249)		
Low HHI	-0.0408	***	-0.0624	-0.1164	***	-0.0249		0.0457
	(0.0050)		(0.0953)	(0.0347)		(0.0217)		
High HHI	0.0036		0.0051	-0.0961	***	-0.0212	0.0273	0.3524
	(0.0088)		(0.1298)	(0.0083)		(0.0249)	(0.0322)	
Low HHI	-0.0408	***	-0.0621	-0.1165	***	-0.0249	0.0022	0.0457
	(0.0050)		(0.0955)	(0.0348)		(0.0217)	(0.0280)	

Notes: This table shows results for the estimated regressions in equation (C.2). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

The quarterly results are reported in Table C.2 and C.3. Qualitatively, the negative impact of a more concentrated portfolio on market downside risk still holds. The realized quantiles do not add much explanatory power to the regressions, since the quantiles are extracted from quarterly returns that are shorter in length and none of the coefficients are significant. For the low-HHI portfolio, interestingly enough, we see that concentration in the top institutions have a significant positive effect on the quantile level of the next period. In contrast, concentration in other institutions will exacerbate the downside risk.

Table C.3: Regression of Conditional Quantile on Decomposed HHI - Quarterly

Panel A: Top 3 Insitutions

	Constant		RQ	HHI_3		HHI_{-3}		LIQ	SMB	R^2	$HHI_3 = HHI_{-3}$
High HHI	0.0077		0.0340	-0.1405	**	-0.0973	***			0.351	0.3517
	(0.0102)		(0.1363)	(-0.0482)		(0.0084)					
Low HHI	-0.0442	***	0.0518	1.4110	**	-0.1837	***			0.0811	0.0006***
	(0.0049)		(0.0994)	(0.4425)		(0.0390)					
High HHI	0.0089		0.0496	-0.1476	**	-0.0967	***	-0.0262		0.3535	0.2789
	(0.0103)		(0.1371)	(0.0487)		(0.0084)		(0.0252)			
Low HHI	-0.0439	***	0.0503	1.3704	**	-0.1809	***	-0.0158		0.0829	0.0009***
	(0.0050)		(0.0995)	(0.4462)		(0.0392)		(0.0215)			
High HHI	0.0092		0.0526	-0.1471	**	-0.0972	***	-0.0255	0.0264	0.3551	0.2885
	(0.0103)		(0.1372)	(0.0487)		(0.0084)		(0.0253)	(0.0322)		
Low HHI	-0.0439	***	0.0503	1.3832	**	-0.1812	***	-0.0159	-0.0074	0.0829	0.0009***
	(0.0050)		(0.0996)	(0.4495)		(0.0393)		(0.0215)	(0.0277)		

Panel B: Top 5 Insitutions

	Constant		RQ	HHI_3		HHI_{-3}		LIQ	SMB	R^2	$HHI_5 = HHI_{-5}$
High HHI	0.0082		0.0424	-0.1378	***	-0.0971				0.3511	0.335
	(0.0104)		(0.1388)	(0.0439)		(0.0083)					
Low HHI	-0.0467	***	0.1724	2.0122	***	-0.2311	***			0.1225	0***
	(0.0049)		(0.1027)	(0.4224)		(0.0401)					
High HHI	0.0095		0.0595	-0.1443	**	-0.0965	***	-0.0264		0.3537	0.2634
	(0.0105)		(0.1397)	(0.0443)		(0.0083)		(0.0252)			
Low HHI	-0.0465	***	0.1702	1.9848	***	-0.2290	***	-0.0091		0.1231	0***
	(0.0049)		(0.1030)	(0.4278)		(0.0404)		(0.0211)			
High HHI	0.0097		0.0610	-0.1429	**	-0.0969	***	-0.0256	0.0253	0.3551	0.2838
	(0.0105)		(0.1398)	(0.0444)		(0.0084)		(0.0253)	(0.0322)		
Low HHI	-0.0465	***	0.1700	1.9895	***	-0.2291	***	-0.0092	-0.0052	0.1232	0***
	(0.0049)		(0.1031)	(0.4292)		(0.0405)		(0.0211)	(0.0270)		

Panel C: Top 10 Insitutions

	Constant		RQ	HHI_{10}		HHI_{-10}		LIQ	SMB	R^2	$HHI_{10} = HHI_{-10}$
High HHI	0.0117		0.1035	-0.1382	***	-0.0953	***			0.3524	0.221
	(0.0114)		(0.1571)	(0.0352)		(0.0083)					
Low HHI	-0.0478	***	0.1148	1.3690	***	-0.2778	***			0.0889	0.0002***
	(0.0051)		(0.1044)	(0.3925)		(0.0540)					
High HHI	0.0129		0.1223	-0.1415	***	-0.0944	***	-0.0257		0.3549	0.1827
	(0.0114)		(0.1581)	(0.0354)		(0.0083)		(0.0251)			
Low HHI	-0.0474	***	0.1125	1.3372	***	-0.2731	***	-0.0163		0.0908	0.0003***
	(0.0052)		(0.1045)	(0.3949)		(0.0543)		(0.0213)			
High HHI	0.0127		0.1187	-0.1393	***	-0.0949	***	-0.0249	0.0229	0.3561	0.2124
	(0.0114)		(0.1584)	(0.0356)		(0.0084)		(0.0251)	(0.0323)		
Low HHI	-0.0474	***	0.1124	1.3380	***	-0.2731	***	-0.0163	-0.0015	0.0908	0.0003***
	(0.0052)		(0.1047)	(0.3960)		(0.0544)		(0.0214)	(0.0274)		

Notes: This table shows results for the estimated regressions in equation (C.3). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. The last column records p-values from testing whether coefficients $HHI_k = HHI_{-k}$, k = 3, 5, 10.

We repeat the regressions in equation (C.2), using the conditional quantile in the first month of each quarter, i.e. January, April, July, and October, as the dependent variable. Our intention is to evaluate the effect of HHI on downside risk in the more immediate future, without imposing the explicit assumption of monthly portfolio turnover. The modified dynamic models for the first quarter, for example, take the form

$$\begin{aligned}
q_{i,Apr}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i,Mar} + b_{i,2}HHI_{i,Q1} + v_{i,Apr} \qquad \text{(C.4)}\\
q_{i,Apr}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i,Mar} + b_{i,2}HHI_{i,Q1} + b_{i,3}Liq_{Q1} + v_{i,Apr}\\
q_{i,Apr}(.05) &= b_{i,0} + b_{i,1}RQ(.05)_{i,Mar} + b_{i,2}HHI_{i,Q1} + b_{i,3}Liq_{Q1} + b_{i,4}SMB_{Q1} + v_{i,Apr}
\end{aligned}$$

We also study the equations with the liquidity and SMB factors from the last quarter as controls, and report the results in Table C.4.

We observe that the realized quantiles of the high-HHI portfolios now have a slightly more prominent positive effect on the downside risk in the next period, which fits our expectation. With the new dynamics, we reach the same conclusion that a higher degree of concentration can be linked to more serious downside risk. The HHI coefficient values suggest that the low-HHI portfolio is more heavily influenced than the high-HHI portfolio when the portfolio holdings are more concentrated in nature. This is consistent with our findings on a quarterly time horizon, and also subject to the caveat that the stocks in question tend to have a more diverse owner base.

C.3 Evidence From Options Markets

We compute risk-neutral variances from a large panel of options data and follow the methodology in Conrad, Dittmar, and Ghysels (2013). We obtain options data from Optionmetrics through Wharton Research Data Services. We restrict our cross-section of firms to be those that we have both investor concentration data through the 13-F filings as well as stock return data (CRSP) and relevant accounting data (COMPUSTAT). Our sample period of daily op-

Table C.4: Regression of Conditional Quantile on HHI - First Month

	Constant	RQ		HHI		LIQ	SMB	R^2
High HHI	-0.0085	0.2522	*	-0.0655	***			0.2611
	(0.0104)	(0.1027)		(0.0066)				
Low HHI	-0.0836	-0.1716		-0.0912	***			0.0819
	(0.0463)	(0.5692)		(0.0184)				
High HHI	-0.0079	0.2587	*	-0.0662	***	0.0231		0.2645
	(0.0105)	(0.1028)		(0.0066)		(0.0205)		
Low HHI	-0.0835	-0.1706		-0.0908	***	-0.0076		0.0831
	(0.0464)	(0.5698)		(0.0184)		(0.0123)		
High HHI	-0.0089	0.2509	*	-0.0655	***	0.0223	-0.0260	0.2671
	(0.0105)	(0.1032)		(0.0067)		(0.0205)	(0.0265)	
Low HHI	-0.0846	-0.1840		-0.0906	***	-0.0078	-0.0039	0.0833
	(0.0466)	(0.5734)		(0.0185)		(0.0123)	(0.0160)	

Notes: This table shows results for the estimated regressions in equation (C.4). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

tions data is from 1996-2013. We follow exactly the methodology in Conrad, Dittmar, and Ghysels (2013) to clean the options data and create risk-neutral variance measures at both a monthly and quarterly frequency. We revisit equation (C.1) using risk neutral variances. The findings appear in the last column of Table C.1 where we study risk neutral variance. The evidence is largely in line with the results using cash market risk measures. This suggests that the effect of HHI also appears in the pricing of derivative contracts. This being said, however, we also ran the same type of regressions with risk neutral skewness measure and did not find a statistically significant relationship of $HHI(3)_{i,t-1}$ on skewness extracted from option markets (detailed results are not reported here).

C.4 HHI Decomposed By Investor Characteristics

We use Brian Bushee's institutional investor classification data to add institutional type and classification at the by-stock/by-year level.[10] We specifically focus on two of his manager-level variables: type (legal type of the institutional investor) and classification (transient, quasi-indexer, and dedicated). The composition of stocks in the high and low HHI portfolios

[10] Data located at `http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html`

Table C.5: Composition of HHI Portfolios by Investor Characteristics

Label	High	Low	Description
		By Type	
BNK	50.31%	99.96%	Bank Trust
INV	43.26%	0.02%	Investment Company
PPS	3.44%	0.00%	Public Pension Fund
CPS	1.69%	0.02%	Corporate (Private) Pension Fund
IIA	1.14%	0.00%	Independent Investment Advisor
INS	0.11%	0.00%	Insurance Company
UFE	0.04%	0.00%	University And Foundation Endowments
MSC	0.01%	0.00%	Miscellaneous
		By Classification	
DED	43.96%	69.02%	Dedicated
QIX	34.12%	30.98%	Quasi-Indexer
TRA	21.92%	0.00%	Transient

Notes: This table shows the time-series average of the percentage of stocks for each legal type and investor classification in the low and high HHI portfolios.

by these two investor characteristics is in Table C.5. The low HHI portfolio is almost entirely comprised of bank trust investors, whereas the high HHI portfolio is dominated by bank trust and investment company investors. The low HHI portfolio is made up of dedicated and quasi-index investors only, while the high HHI portfolio has a more even distribution across classifications. We present the conditional volatility results using HHI decomposed according to investor type and classification below in Tables C.6 and C.7. The models for HHI decomposed by classification are as below (analogous for investor type):

$$\begin{aligned}
\hat{\sigma}^2_{i,t} &= b_{i,0} + b_{i,1}\hat{\sigma}^2_{i,t-1} + \sum_{class} b_{i,class} HHI(class)_{i,t} + v_{i,t} \qquad \text{(C.5)}\\
\hat{\sigma}^2_{i,t} &= b_{i,0} + b_{i,1}\hat{\sigma}^2_{i,t-1} + \sum_{class} b_{i,class} HHI(class)_{i,t} + b_{i,3}Liq_t + v_{i,t}\\
\hat{\sigma}^2_{i,t} &= b_{i,0} + b_{i,1}\hat{\sigma}^2_{i,t-1} + \sum_{class} b_{i,class} HHI(class)_{i,t} + b_{i,3}Liq_t + b_{i,4}SMB_t + v_{i,t}
\end{aligned}$$

As we noted before, the impact of decomposed HHI along the investor type and classification is not statistically significant, both for the conditional volatility results as well as for additional risk measures.

Table C.6: Conditional Volatility by HHI Decomposition by Investor Type

	Cons.	$\hat{\sigma}^2_{i,t-1}$	BNK	INS	INV	IIA	CPS	PPS	UFE	MSC	LIQ	SMB	R^2
High	−0.01	0.12	0.01	−0.03	0.01	−0.01	0.01	0.01	−0.13	0.70			0.04
	[−0.30]	[1.34]	[0.89]	[−0.50]	[0.79]	[−0.97]	[0.20]	[0.89]	[−1.13]	[0.19]			
Low	0.01	0.45	0.01	−110.61	−1.43		0.52		−718.67				0.22
	[1.42]	[7.22]	[0.06]	[−3.32]	[−2.68]		[2.88]		[−3.49]				
High	−0.01	0.14	0.01	−0.04	0.01	−0.01	−0.01	0.01	−0.10	0.50	0.01		0.05
	[−0.06]	[1.53]	[0.62]	[−0.60]	[0.51]	[−1.09]	[−0.02]	[0.57]	[−1.19]	[0.13]	[0.69]		
Low	0.01	0.48	0.01	−85.88	−1.17		0.50		−864.86		0.01		0.26
	[0.73]	[5.56]	[0.19]	[−0.30]	[−0.55]		[0.70]		[−0.45]		[2.54]		
High	−0.01	0.14	0.01	−0.04	0.01	−0.01	−0.01	0.01	−0.10	0.53	0.01	0.01	0.05
	[−0.03]	[1.30]	[0.57]	[−0.55]	[0.47]	[−1.09]	[−0.02]	[0.52]	[−1.24]	[0.14]	[0.66]	[0.28]	
Low	0.01	0.44	0.01	−185.57	−0.85		0.60		−388.35		0.01	0.01	0.29
	[0.72]	[4.90]	[0.28]	[−0.66]	[−0.41]		[0.86]		[−0.20]		[2.46]	[2.05]	

Notes: This table shows the time-series average of the percentage of stocks for each legal type and investor classification in the low and high HHI portfolios. Results are in estimate and t-statistic row pairs, where t-statsitics are formed using Newey and West (1987) standard errors. Certain type categories were dropped from the low HHI models due to an insufficient number of stocks in that category.

Table C.7: Conditional Volatility by HHI Decomposition by Investor Classification

	Cons.	CV(-1)	DED	QIX	TRA	LIQ	SMB	R^2
High	0.01	0.09	−0.01	−0.01	−0.00			0.03
	[1.82]	[1.14]	[−1.43]	[−1.18]	[−1.06]			
Low	0.00	0.47	0.00	0.01	−40.03			0.21
	[2.03]	[7]	[0.86]	[1.17]	[−2.45]			
High	0.01	0.11	−0.01	−0.01	−0.01	0.01		0.04
	[2.2]	[1.12]	[−1.76]	[−1.5]	[−1.54]	[0.67]		
Low	0.00	0.52	0.01	0.01	−38.55	0.00		0.26
	[0.89]	[6.68]	[0.98]	[1.09]	[−1.37]	[1.51]		
High	0.01	0.10	−0.01	−0.01	−0.01	0.01	0.00	0.04
	[2.16]	[1.04]	[−1.75]	[−1.5]	[−1.51]	[0.67]	[0.41]	
Low	0.00	0.47	0.01	0.01	−20.21	0.00	0.00	0.29
	[1.06]	[5.07]	[1.27]	[1.34]	[−0.95]	[1.62]	[1.57]	

Notes: This table shows the time-series average of the percentage of stocks for each investor classification in the low and high HHI portfolios. Results are in estimate and t-statistic row pairs, where t-statsitics are formed using Newey and West (1987) standard errors.

D Value-Weighted Portfolio

We perform another set of robustness checks by examining the value-weighted HHI portfolios. All analyses we performed using equal-weighted portfolios are replicated using value-weighted returns. Overall we find that our main conditional volatility and downside risk results are robust to the choice of equal- versus value- weighted returns.

Table D.1: Annualized HHI Low-High Portfolio Returns - VW

Mean	Median	Std. Dev.	Skew	Kurt.	25 %	75 %
0.76	2.23	6.95	-0.57	5.00	-6.35	7.73

Notes: This table shows summary statistics of annualized percentage value-weighted returns from the Low-Minus-High (LMH) portfolio we constructed. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

Table D.2: Annualized Portfolio Returns – VW

Portfolio	1	2	3	4	5	Low-High (LMH)
Mean	4.9357	5.3476	4.9978	5.7891	5.6984	0.7627
Median	5.7736	5.7443	5.2192	6.5754	6.8490	2.2278
Std. Dev.	9.4950	6.4525	6.8238	6.4698	5.5405	6.9461
Skewness	-0.2660	-0.2718	-0.2938	-0.2484	-0.5094	-0.5659
Kurtosis	4.3092	3.3106	4.1885	4.0530	3.9438	4.9955
25% Perc.	-4.2011	-1.1747	-1.8955	-0.6152	0.1144	-6.3473
75% Perc.	14.8857	13.4917	12.1572	12.6247	12.8116	7.7251

Notes: This table shows descriptive statistics of annualized portfolio returns in percentages. Portfolio returns are value-weighted. We report values for the 5 HHI portfolios as well as the Low-Minus-High (LMH) portfolio. Quarterly sample starts in 1980Q1 and ends in 2019Q1.

Figure D.2 illustrates the 5% quantiles of the high-HHI portfolio and the low-HHI portfolio, which serves as a comparison to Figure 4 in the paper. The graph clearly suggests that for value-weighted construction, the high-HHI portfolio is subject to a higher level of tail risk.

We retain negative signs for the HHI coefficient terms when repeating the conditional quantile exercises, although in some cases the results are less significant than the equal-weighted scenario. Qualitatively speaking, a higher degree of holding concentration intensifies downside risks even as we change the portfolio composition methodology. We also

Table D.3: Conditional Mean Linear Factor Models - VW

	Rm-Rf		SMB		HML		LIQ		PC-HHI
	FF3 - GMM J-stat p-val 0.00								
Betas									
1 (High HHI)	0.350	***	0.179	***	0.107	***			
	(0.027)		(0.043)		(0.033)				
2	0.310	***	0.073	***	0.044	*			
	(0.011)		(0.023)		(0.026)				
3	0.332	***	0.116	***	0.012				
	(0.014)		(0.026)		(0.030)				
4	0.340	***	0.069	***	0.004				
	(0.010)		(0.017)		(0.031)				
5 (Low HHI)	0.305	***	0.020	**	-0.014				
	(0.008)		(0.010)		(0.013)				
Price of Risk	0.050	***	-0.036	*	0.013				
	(0.007)		(0.020)		(0.016)				
	FF3+Liquidity - GMM J-stat p-val 0.00								
Betas									
1 (High HHI)	0.363	***	0.156	***	0.112	***	0.084	**	
	(0.037)		(0.049)		(0.032)		(0.034)		
2	0.311	***	0.082	***	0.043	**	0.042	***	
	(0.018)		(0.026)		(0.020)		(0.016)		
3	0.340	***	0.107	***	0.016		0.039	**	
	(0.015)		(0.028)		(0.027)		(0.015)		
4	0.320	***	0.119	***	-0.004		0.025	**	
	(0.011)		(0.020)		(0.021)		(0.010)		
5 (Low HHI)	0.321	***	-0.016	**	-0.008		0.017	***	
	(0.006)		(0.008)		(0.010)		(0.006)		
Price of Risk	0.077		0.029		0.198		-0.503		
	(0.098)		(0.093)		(0.697)		(1.536)		
	FF3+Liquidity+HHI - GMM J-stat p-val 0.00								
Betas									
1 (High HHI)	0.366	***	0.147	***	0.110	***	0.085	**	0.009
	(0.043)		(0.057)		(0.040)		(0.043)		(0.015)
2	0.315	***	0.069	**	0.044	*	0.030		0.013
	(0.019)		(0.032)		(0.026)		(0.020)		(0.008)
3	0.342	***	0.099	***	0.015		0.035	**	0.009
	(0.015)		(0.028)		(0.026)		(0.016)		(0.006)
4	0.321	***	0.115	***	-0.005		0.023		0.004
	(0.012)		(0.025)		(0.021)		(0.016)		(0.005)
5 (Low HHI)	0.321	***	-0.017	*	-0.010		0.019	***	0.001
	(0.006)		(0.009)		(0.011)		(0.006)		(0.003)
Price of Risk	0.066		0.014		0.116		-0.269		-0.410
	(0.043)		(0.046)		(0.268)		(0.539)		(0.572)

Notes: This table shows GMM estimation results for the system in equation (3). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Portfolio returns are value-weighted. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.4: Conditional Volatility Regressions – Quarterly – VW

	Constant	$\hat{\sigma}^2_{i,t-1}$	HHI	LIQ	SMB	R^2
1 (high HHI)	−0.0005	0.8356***	0.0009			0.7254
	(0.0005)	(0.0405)	(0.0006)			
5 (low HHI)	0.0016	0.3459***	−0.0334			0.1301
	(0.0011)	(0.0827)	(0.0308)			
1 (high HHI)	−0.0009	0.8306***	0.0014*	−0.0038		0.7434
	(0.0007)	(0.0420)	(0.0008)	(0.0023)		
5 (low HHI)	0.0015	0.3583***	−0.0302	−0.0007		0.1352
	(0.0011)	(0.1034)	(0.0311)	(0.0013)		
1 (high HHI)	−0.0013*	0.8504***	0.0019**	−0.0040*	−0.0057***	0.7673
	(0.0008)	(0.0442)	(0.0009)	(0.0024)	(0.0018)	
5 (low HHI)	0.0011	0.4286***	−0.0195	−0.0010	−0.0036***	0.2054
	(0.0010)	(0.0972)	(0.0284)	(0.0013)	(0.0011)	

Notes: This table shows estimation results for the regressions in (C.5). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Returns are value-weighted. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Newey-West standard errors appear in parentheses.

Table D.5: Conditional Volatility Regressions – Monthly – VW

	Constant	$\hat{\sigma}^2_{i,t-1}$	HHI	LIQ	SMB	R^2
1 (high HHI)	−0.0064	0.3739***	0.0101**			0.1985
	(0.0043)	(0.1198)	(0.0048)			
5 (low HHI)	0.0045***	0.1099	−0.0367			0.0195
	(0.0018)	(0.1063)	(0.0366)			
1 (high HHI)	−0.0071	0.3626***	0.011**	−0.0074		0.2013
	(0.0052)	(0.1154)	(0.0058)	(0.0159)		
5 (low HHI)	0.0044***	0.1028	−0.0343	−0.0057		0.0253
	(0.0017)	(0.1067)	(0.0365)	(0.0114)		
1 (high HHI)	−0.0073	0.3706***	0.0113*	−0.0065	−0.0144	0.2082
	(0.0052)	(0.1156)	(0.0058)	(0.0153)	(0.0160)	
5 (low HHI)	0.0046***	0.1425	−0.0397	−0.0042	−0.0223	0.0797
	(0.0017)	(0.0988)	(0.0359)	(0.0097)	(0.0137)	

Notes: This table shows estimation results for the regressions in (C.5). Conditional volatilities are produced for the first mont in each calendar quarter. Quarterly sample starts in 1980Q1 and ends in 2019Q1. Returns are value-weighted. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Newey-West standard errors appear in parentheses.

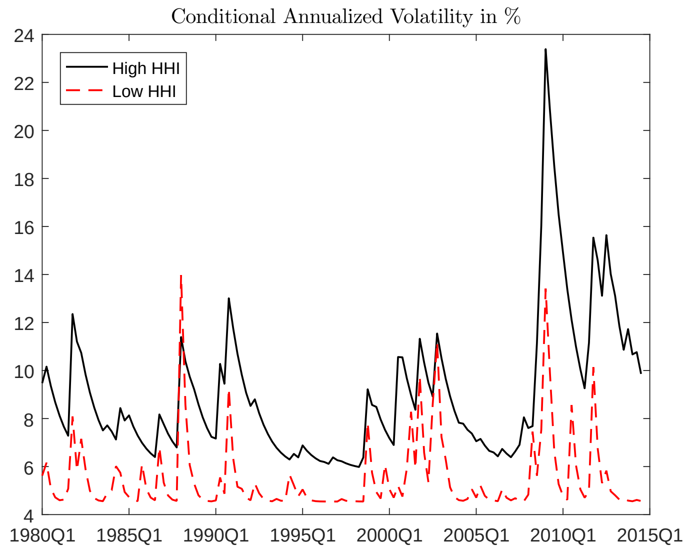
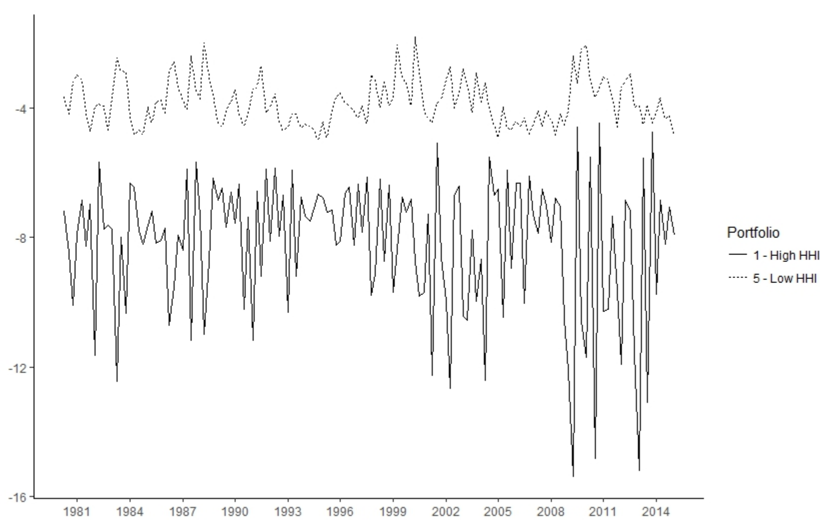


Fig. D.1: Conditional Volatility High versus Low HHI Portfolio – VW

Fig. D.2: Conditional Quantile Estimates HHI Portfolios 5% Left Tail, Value-Weighted



present regression outputs for decomposed HHI and the pre-crisis period, and note that our previous findings are consistently supported.

Table D.6: Regression of Conditional Quantile on HHI, Value-Weighted

	Constant		HHI		LIQ	SMB	R^2
High HHI	-0.0109	**	-0.0714	***			0.3973
	(0.0041)		(0.0053)				
Low HHI	-0.0380	***	0.0214				0.0109
	(0.0011)		(0.0123)				
High HHI	-0.0109	**	-0.0715	***	0.0061		0.3976
	(0.0041)		(0.0053)		(0.0172)		
Low HHI	-0.0379	***	0.0217		-0.0060		0.0126
	(0.0011)		(0.0123)		(0.0086)		
High HHI	-0.0106	*	-0.0722	***	0.0070	0.0305	0.4017
	(0.0041)		(0.0053)		(0.0172)	(0.0222)	
Low HHI	-0.0379	***	0.0214		-0.0057	0.0100	0.0155
	(0.0011)		(0.0123)		(0.0086)	(0.0111)	

Notes: This table shows results for the estimated regressions in equation (6). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.7: Regression of Conditional Quantile on Decomposed HHI, Value-Weighted

Panel A: Top 3 Insitutions

	Constant		HHI_3		HHI_{-3}		LIQ	SMB	R^2	$HHI_3 = HHI_{-3}$
High HHI	-0.0108	*	-0.0753	*	-0.0714	***			0.3973	0.8913
	(0.0043)		(0.0292)		(0.0053)					
Low HHI	-0.0365	***	-0.2057		0.0314	*			0.0219	0.0792
	(0.0014)		(0.1295)		(0.0135)					
High HHI	-0.0108	*	-0.0753	*	-0.0716	***	0.0061		0.3976	0.8958
	(0.0043)		(0.0292)		(0.0053)		(0.0172)			
Low HHI	-0.0365	***	-0.2000		0.0314	*	-0.0049		0.0230	0.0879
	(0.0014)		(0.1301)		(0.0135)		(0.0086)			
High HHI	-0.0104	*	-0.0760	**	-0.0723	***	0.0070	0.0305	0.4017	0.8949
	(0.0043)		(0.0292)		(0.0054)		(0.0172)	(0.0222)		
Low HHI	-0.0364	***	-0.2074		0.0313	*	-0.0046	0.0110	0.0265	0.0789
	(0.0014)		(0.1303)		(0.0135)		(0.0086)	(0.0111)		

Panel B: Top 5 Insitutions

	Constant		HHI_5		HHI_{-5}		LIQ	SMB	R^2	$HHI_5 = HHI_{-5}$
High HHI	-0.0114	**	-0.0626	**	-0.0713	***			0.3976	0.6969
	(0.0042)		(0.0231)		(0.0053)					
Low HHI	-0.0370	***	-0.0898		0.0305	*			0.0143	0.3257
	(0.0015)		(0.1136)		(0.0153)					
High HHI	-0.0114	**	-0.0624	**	-0.0714	***	0.0064		0.3979	0.6862
	(0.0042)		(0.0231)		(0.0053)		(0.0172)			
Low HHI	-0.0370	***	-0.0859		0.0305	*	-0.0056		0.0158	0.3428
	(0.0015)		(0.1139)		(0.0153)		(0.0086)			
High HHI	-0.0111	**	-0.0607	**	-0.0721	***	0.0074	0.0313	0.4022	0.6108
	(0.0042)		(0.0231)		(0.0053)		(0.0172)	(0.0223)		
Low HHI	-0.0369	***	-0.0973		0.0310	*	-0.0053	0.0111	0.0194	0.2981
	(0.0015)		(0.1145)		(0.0154)		(0.0086)	(0.0111)		

Panel C: Top 10 Insitutions

	Constant		HHI_{10}		HHI_{-10}		LIQ	SMB	R^2	$HHI_{10} = HHI_{-10}$
High HHI	-0.0116	**	-0.0605	***	-0.0715	***			0.3982	0.5166
	(0.0042)		(0.0175)		(0.0053)					
Low HHI	-0.0366	***	-0.0924		0.0390	*			0.0172	0.184
	(0.0015)		(0.0863)		(0.0180)					
High HHI	-0.0115	**	-0.0606	***	-0.0717	***	0.0062		0.3985	0.5152
	(0.0042)		(0.0175)		(0.0053)		(0.0172)			
Low HHI	-0.0366	***	-0.0905		0.0391	*	-0.0056		0.0187	0.191
	(0.0015)		(0.0865)		(0.0180)		(0.0086)			
High HHI	-0.0112	**	-0.0610	***	-0.0724	***	0.0071	0.0307	0.4026	0.5014
	(0.0042)		(0.0175)		(0.0053)		(0.0172)	(0.0222)		
Low HHI	-0.0365	***	-0.0961		0.0395	*	-0.0054	0.0109	0.0221	0.1721
	(0.0015)		(0.0867)		(0.0180)		(0.0086)	(0.0111)		

Notes: This table shows results for the estimated regressions in equation (7). Quarterly sample starts in 1980Q1 and ends in 2019Q1. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. The last column records p-values from testing whether coefficients $HHI_k = HHI_{-k}$, k = 3, 5, 10.

Table D.8: Regression of Conditional Quantile on HHI: Pre-crisis, Value-Weighted

	Constant		HHI		LIQ	SMB	R^2
High HHI	-0.0190	***	-0.0613	***			0.3973
	(0.0039)		(0.0051)				
Low HHI	-0.0383	***	0.0220				0.0146
	(0.0011)		(0.0123)				
High HHI	-0.0189	***	-0.0618	***	0.0154		0.3991
	(0.0039)		(0.0052)		(0.01884)		
Low HHI	-0.0380	***	0.0225		-0.0162		0.0260
	(0.0011)		(0.0122)		(0.0102)		
High HHI	-0.0185	***	-0.0627	***	0.0165	0.0264	0.4037
	(0.0039)		(0.0052)		(0.0188)	(0.0206)	
Low HHI	-0.0381	***	0.0221		-0.0159	0.0115	0.0308
	(0.0011)		(0.0122)		(0.0102)	(0.0111)	

Notes: This table shows results for the estimated regressions in equation (6). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.9. Regression of Conditional Quantile on Quarterly HHI - Pre-crisis, Value-Weighted

	Constant		RQ		HHI		LIQ	SMB	R^2
High HHI	-0.0062		0.4163	***	-0.0512	***			0.4421
	(0.0048)		(0.0996)		(0.0055)				
Low HHI	-0.0449	***	-0.2888	***	-0.0116				0.0713
	(0.0021)		(0.0793)		(0.0151)				
High HHI	-0.0062		0.4119	***	-0.0516	***	0.0077		0.4426
	(0.0049)		(0.1004)		(0.0056)		(0.0183)		
Low HHI	-0.0447	***	-0.2925	***	-0.0115		-0.0172		0.0842
	(0.0021)		(0.0789)		(0.0150)		(0.0099)		
High HHI	-0.0060		0.4087	***	-0.0525	***	0.0088	0.0243	0.4464
	(0.0049)		(0.1003)		(0.0056)		(0.0183)	(0.0199)	
Low HHI	-0.0447	***	-0.2905	***	-0.0117		-0.0169	0.0104	0.0881
	(0.0021)		(0.0790)		(0.0150)		(0.0099)	(0.0108)	

Notes: This table shows results for the estimated regressions in equation (C.2). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.10. Regression of Conditional Quantile on Decomposed HHI - Pre-crisis, Value-Weighted

Panel A: Top 3 Insitutions

	Constant		HHI_3		HHI_{-3}		LIQ	SMB	R^2	$HHI_3 = HHI_{-3}$
High HHI	-0.0162	***	-0.1391	***	-0.0621	***			0.4081	0.0478*
	(0.0041)		(0.0394)		(0.0051)					
Low HHI	-0.0388	***	0.1063		0.0178				0.0163	0.5369
	(0.0014)		(0.1369)		(0.0141)					
High HHI	-0.0162	***	-0.1364	***	-0.0624	***	0.0104		0.4089	0.0601
	(0.0041)		(0.0398)		(0.0051)		(0.0189)			
Low HHI	-0.0386	***	0.1171		0.0178		-0.0165		0.0282	0.4876
	(0.0014)		(0.1365)		(0.0140)		(0.0102)			
High HHI	-0.0159	***	-0.1361	***	-0.0632	***	0.0115	0.0255	0.4131	0.0639
	(0.0041)		(0.0398)		(0.0052)		(0.0189)	(0.0205)		
Low HHI	-0.0386	***	0.1101		0.0177		-0.0162	0.0111	0.0326	0.5188
	(0.0014)		(0.1367)		(0.0140)		(0.0102)	(0.0112)		

Panel B: Top 5 Insitutions

	Constant		HHI_5		HHI_{-5}		LIQ	SMB	R^2	$HHI_5 = HHI_{-5}$
High HHI	-0.0183	***	-0.0810	**	-0.0611	***			0.3990	0.4282
	(0.0040)		(0.0253)		(0.0051)					
Low HHI	-0.0385	***	0.0477		0.0197				0.0148	0.8216
	(0.0014)		(0.1143)		(0.0159)					
High HHI	-0.0183	***	-0.0788	**	-0.0616	***	0.0135		0.4004	0.4972
	(0.0040)		(0.0255)		(0.0052)		(0.0191)			
Low HHI	-0.0383	***	0.0590		0.0193		-0.0164		0.0264	0.7479
	(0.0014)		(0.1141)		(0.0158)		(0.0102)			
High HHI	-0.0180	***	-0.0758	**	-0.0624	***	0.0149	0.0250	0.4044	0.6024
	(0.0040)		(0.0256)		(0.0052)		(0.0191)	(0.0208)		
Low HHI	-0.0383	***	0.0481		0.0198		-0.0160	0.0112	0.0310	0.8195
	(0.0014)		(0.1147)		(0.0158)		(0.0102)	(0.0112)		

Panel C: Top 10 Insitutions

	Constant		HHI_{10}		HHI_{-10}		LIQ	SMB	R^2	$HHI_{10} = HHI_{-10}$
High HHI	-0.0189	***	-0.0649	***	-0.0611	***			0.3974	0.8318
	(0.0039)		(0.0180)		(0.0052)					
Low HHI	-0.0382	***	0.0154		0.0231				0.0146	0.942
	(0.0015)		(0.0921)		(0.0192)					
High HHI	-0.0188	***	-0.0640	***	-0.0617	***	0.0151		0.3992	0.9023
	(0.0040)		(0.0180)		(0.0053)		(0.0190)			
Low HHI	-0.0380	***	0.0228		0.0225		-0.0162		0.0260	0.9976
	(0.0015)		(0.0919)		(0.0191)		(0.0102)			
High HHI	-0.0185	***	-0.0636	***	-0.0626	***	0.0163	0.0264	0.4037	0.9545
	(0.0040)		(0.0180)		(0.0053)		(0.0190)	(0.0207)		
Low HHI	-0.0380	***	0.0168		0.0230		-0.0159	0.0115	0.0308	0.9535
	(0.0015)		(0.0921)		(0.0191)		(0.0102)	(0.0112)		

Notes: This table shows results for the estimated regressions in equation (7). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. The last column records p-values from testing whether coefficients $HHI_k = HHI_{-k}$, k = 3, 5, 10.

Table D.11: Regression of Conditional Quantile on Quarterly Decomposed HHI - Pre-crisis, Value-Weighted

Panel A: Top 3 Insitutions

	Constant	RQ	HHI_3	HHI_{-3}	LIQ	SMB	R^2	$HHI_3 = HHI_{-3}$
High HHI	-0.0038	0.4081***	-0.1225**	-0.0522***			0.4511	0.0615
	(0.0050)	(0.0992)	(0.0383)	(0.0055)				
Low HHI	-0.0448***	-0.3120***	-0.1204	-0.0090			0.0737	0.4573
	(0.0021)	(0.0853)	(0.1469)	(0.0155)				
High HHI	-0.0039	0.4065***	-0.1217**	-0.0523***	0.0031		0.4512	0.0680
	(0.0050)	(0.0999)	(0.0386)	(0.0056)	(0.0184)			
Low HHI	-0.0446***	-0.3135***	-0.1106	-0.0092	-0.0169		0.0861	0.4969
	(0.0021)	(0.0849)	(0.1463)	(0.0154)	(0.0099)			
High HHI	-0.0036	0.4034***	-0.1215**	-0.0531***	0.0042	0.0235	0.4548	0.0719
	(0.0050)	(0.0998)	(0.0386)	(0.0056)	(0.0184)	(0.0198)		
Low HHI	-0.0446***	-0.3127***	-0.1168	-0.0092	-0.0166	0.0108	0.0903	0.4716
	(0.0021)	(0.0849)	(0.1465)	(0.0154)	(0.0099)	(0.0108)		

Panel B: Top 5 Insitutions

	Constant	RQ	HHI_5	HHI_{-5}	LIQ	SMB	R^2	$HHI_5 = HHI_{-5}$
High HHI	-0.0049	0.4242***	-0.0779**	-0.0508***			0.4454	0.2627
	(0.0050)	(0.0998)	(0.0244)	(0.0055)				
Low HHI	-0.0448***	-0.3409***	-0.1910	-0.0024			0.0800	0.1546
	(0.0021)	(0.0871)	(0.1264)	(0.0164)				
High HHI	-0.0050	0.4213***	-0.0772**	-0.0511***	0.0046		0.4455	0.2868
	(0.0050)	(0.1007)	(0.0246)	(0.0056)	(0.0185)			
Low HHI	-0.0446***	-0.3413***	-0.1798	-0.0028	-0.0165		0.0918	0.1804
	(0.0021)	(0.0868)	(0.1261)	(0.0163)	(0.0099)			
High HHI	-0.0049	0.4172***	-0.0745**	-0.0519***	0.0060	0.0219	0.4486	0.3602
	(0.0050)	(0.1007)	(0.0247)	(0.0056)	(0.0185)	(0.0201)		
Low HHI	-0.0446***	-0.3425***	-0.1921	-0.0024	-0.0161	0.0118	0.0968	0.1525
	(0.0021)	(0.0867)	(0.1265)	(0.0163)	(0.0099)	(0.0108)		

Panel C: Top 10 Insitutions

	Constant	RQ	HHI_{10}	HHI_{-10}	LIQ	SMB	R^2	$HHI_{10} = HHI_{-10}$
High HHI	-0.0057	0.4202***	-0.0600***	-0.0506***			0.4429	0.5948
	(0.0049)	(0.1001)	(0.0173)	(0.0056)				
Low HHI	-0.0446***	-0.3543***	-0.1930	0.0087			0.0848	0.0755
	(0.0021)	(0.0870)	(0.1026)	(0.0189)				
High HHI	-0.0058	0.4162***	-0.0596***	-0.0510***	0.0067		0.4432	0.6283
	(0.0050)	(0.1009)	(0.0174)	(0.0057)	(0.0185)			
Low HHI	-0.0444***	-0.3554***	-0.1861	0.0081	-0.0165		0.0967	0.086
	(0.0021)	(0.0867)	(0.1023)	(0.0188)	(0.0098)			
High HHI	-0.0056	0.4125***	-0.0594***	-0.0519***	0.0078	0.0238	0.4469	0.675
	(0.0050)	(0.1009)	(0.0174)	(0.0058)	(0.0185)	(0.0200)		
Low HHI	-0.0444***	-0.3553***	-0.1920	0.0086	-0.0162	0.0114	0.1014	0.0766
	(0.0021)	(0.0866)	(0.1024)	(0.0188)	(0.0098)	(0.0108)		

Notes: This table shows results for the estimated regressions in equation (C.3). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. The last column records p-values from testing whether coefficients $HHI_k = HHI_{-k}$, k = 3, 5, 10.

E Pre-Crisis Period

We repeat the conditional quantile exercise in equation (6) in the paper with data prior to the global financial crisis (1980Q1-2007Q2) and report results in Table E.1. Notably the estimates for the high-HHI portfolio are similar across specification, an indication that our results are not driven by the recent financial crisis. The low-HHI portfolio estimates continue to display a lack of statistical significance.

Table E.1: Regression of Conditional Quantile on HHI: Pre-crisis

	Constant		HHI		LIQ	SMB	R^2
1 (high HHI)	0.0500		-0.1478	***			0.2052
	(0.0267)		(0.0280)				
5 (low HHI)	-0.0273		-0.2715				0.0073
	(0.0149)		(0.3054)				
1 (high HHI)	0.0514		-0.1493	***	0.0054		0.2056
	(0.0276)		(0.0292)		(0.0264)		
5 (low HHI)	-0.0243		-0.3137		-0.0506		0.0280
	(0.0149)		(0.3049)		(0.0335)		
1 (high HHI)	0.0583	*	-0.1569	***	0.0082	0.0398	0.2201
	(0.0280)		(0.0295)		(0.0264)	(0.0283)	
5 (low HHI)	-0.0246		-0.3089		-0.0503	0.0126	0.0291
	(0.0150)		(0.3065)		(0.0337)	(0.0368)	

Notes: This table shows results for the estimated regressions in equation (6). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

E.1 Downside Risk with Decomposed HHI

We also replicate the regressions in Section C for the pre-crisis period, and report the outputs in this section. Table E.2, E.3, and E.4 contain results of dynamic models on a quarterly frequency, whereas regression outputs of conditional quantiles from the first month of each quarter on HHI are presented in Table E.5. We reach the conclusion that the effect of HHI on downside risk retains the same pattern during the sub-sample before the financial crisis.

Table E.2: Regression of Conditional Quantile on Quarterly HHI - Pre-crisis

	Constant		RQ	HHI		LIQ		SMB	R^2
High HHI	-0.0123		-0.2111	-0.0918	***				0.4157
	(0.0105)		(0.1685)	(0.0074)					
Low HHI	-0.0423	***	-0.1685	-0.1434	***				0.0688
	(0.0054)		(0.1189)	(0.0359)					
High HHI	-0.0129		-0.2191	-0.0912	***	-0.0181			0.4169
	(0.0106)		(0.1691)	(0.0075)		(0.0273)			
Low HHI	-0.0420	***	-0.1860	-0.1444	***	-0.0519	*		0.0868
	(0.0054)		(0.1183)	(0.0357)		(0.0252)			
High HHI	-0.0124		-0.2129	-0.0915	***	-0.0176		0.0121	0.4173
	(0.0107)		(0.1701)	(0.0075)		(0.0273)		(0.0299)	
Low HHI	-0.0420	***	-0.1849	-0.1445	***	-0.0518	*	0.0041	0.0869
	(0.0054)		(0.1188)	(0.0358)		(0.0252)		(0.0276)	

Notes: This table shows results for the estimated regressions in equation (C.2). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table E.3: Regression of Conditional Quantile on Decomposed HHI - Pre-crisis

Panel A: Top 3 Insitutions

	Constant		HHI_3		HHI_{-3}		LIQ	SMB	R^2	$HHI_3 = HHI_{-3}$
High HHI	0.0018		-0.1403	**	-0.0918	***			0.4151	0.2447
	(0.0064)		(0.0432)		(0.0074)					
Low HHI	-0.0422	***	1.4495	***	-0.2201	***			0.1203	0.002***
	(0.0035)		(0.4091)		(0.0406)					
High HHI	0.0022		-0.1485	***	-0.0912	***	-0.0245		0.4172	0.1816
	(0.0064)		(0.0443)		(0.0074)		(0.0280)			
Low HHI	-0.0413	***	1.3713	**	-0.2142	***	-0.0377		0.1297	0.0003***
	(0.0036)		(0.4110)		(0.0407)		(0.0247)			
High HHI	0.0023		-0.1478	**	-0.0916	***	-0.0238	0.0132	0.4177	0.1917
	(0.0065)		(0.0444)		(0.0075)		(0.0281)	(0.0298)		
Low HHI	-0.0413	***	1.3755	**	-0.2143	***	-0.0377	-0.0027	0.1297	0.0004***
	(0.0036)		(0.4141)		(0.0408)		(0.0248)	(0.0271)		

Panel B: Top 5 Insitutions

	Constant		HHI_5		HHI_{-5}		LIQ	SMB	R^2	$HHI_5 = HHI_{-5}$
High HHI	0.0021		-0.1399	***	-0.0916	***			0.4158	0.2043
	(0.0064)		(0.0394)		(0.0074)					
Low HHI	-0.0480	***	2.1568	***	-0.3068	***			0.1689	0***
	(0.0038)		(0.4287)		(0.0464)					
High HHI	0.0025		-0.1479	***	-0.0909	***	-0.0255		0.4181	0.147
	(0.0064)		(0.0404)		(0.0074)		(0.0280)			
Low HHI	-0.0471	***	2.0849	***	-0.3000	***	-0.0346		0.1768	0***
	(0.0039)		(0.4306)		(0.0465)		(0.0240)			
High HHI	0.0026		-0.1467	***	-0.0912	***	-0.0248	0.0114	0.4185	0.1604
	(0.0064)		(0.0406)		(0.0075)		(0.0281)	(0.0299)		
Low HHI	-0.0471	***	2.0865	***	-0.3001	***	-0.0346	-0.0015	0.1768	0***
	(0.0039)		(0.4324)		(0.0466)		(0.0241)	(0.0262)		

Panel C: Top 10 Insitutions

	Constant		HHI_{10}		HHI_{-10}		LIQ	SMB	R^2	$HHI_{10} = HHI_{-10}$
High HHI	0.0024		-0.1404	***	-0.0897	***			0.4191	0.0932
	(0.0062)		(0.0304)		(0.0073)					
Low HHI	-0.0477	***	1.4382	***	-0.3392	***			0.1246	0.0001***
	(0.0043)		(0.3915)		(0.0629)					
High HHI	0.0026		-0.1444	***	-0.0888	***	-0.0247		0.4212	0.0701
	(0.0062)		(0.0308)		(0.0074)		(0.0275)			
Low HHI	-0.0466	***	1.3804	***	-0.3300	***	-0.0404		0.1355	0.0002***
	(0.0043)		(0.3915)		(0.0629)		(0.0245)			
High HHI	0.0026		-0.1435	***	-0.0890	***	-0.0242	0.0065	0.4214	0.0810
	(0.0062)		(0.0312)		(0.0075)		(0.0277)	(0.0301)		
Low HHI	-0.0466	***	1.3786	***	-0.3300	***	-0.0403	0.0040	0.1356	0.0002***
	(0.0043)		(0.3926)		(0.0630)		(0.0246)	(0.0269)		

Notes: This table shows results for the estimated regressions in equation (7). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. The last column records p-values from testing whether coefficients $HHI_k = HHI_{-k}$, k = 3, 5, 10.

Table E.4: Regression of Conditional Quantile on Quarterly Decomposed HHI - Pre-crisis

Panel A: Top 3 Insitutions

	Constant	RQ	HHI_3	HHI_{-3}	LIQ	SMB	R^2	$HHI_3 = HHI_{-3}$
High HHI	-0.0085	-0.1919	-0.1361**	-0.0928***			0.4186	0.3011
	(0.0112)	(0.1694)	(0.0434)	(0.0075)				
Low HHI	-0.0434***	-0.0361	1.4060**	-0.2223***			0.1207	0.0004***
	(0.0053)	(0.1216)	(0.4354)	(0.0414)				
High HHI	-0.0085	-0.1994	-0.1447**	-0.0922***	-0.0260		0.4209	0.2225
	(0.0112)	(0.1697)	(0.0444)	(0.0075)	(0.0280)			
Low HHI	-0.0431***	-0.0584	1.2980**	-0.2176***	-0.0391		0.1306	0.0012***
	(0.0053)	(0.1220)	(0.4393)	(0.0413)	(0.0249)			
High HHI	-0.0082	-0.1943	-0.1442**	-0.0925***	-0.0255	0.0103	0.4212	0.2306
	(0.0112)	(0.1707)	(0.0445)	(0.0075)	(0.0281)	(0.0299)		
Low HHI	-0.0431***	-0.0588	1.3023**	-0.2177***	-0.0391	-0.0032	0.1307	0.0012***
	(0.0053)	(0.1224)	(0.4419)	(0.0415)	(0.0250)	(0.0271)		

Panel B: Top 5 Insitutions

	Constant	RQ	HHI_5	HHI_{-5}	LIQ	SMB	R^2	$HHI_5 = HHI_{-5}$
High HHI	-0.0080	-0.1849	-0.1351***	-0.0926***			0.419	0.2682
	(0.0112)	(0.1700)	(0.0397)	(0.0074)				
Low HHI	-0.0481***	-0.0016	2.1549***	-0.3069***			0.1689	0***
	(0.0052)	(0.1172)	(0.4519)	(0.0467)				
High HHI	-0.0079	-0.1913	-0.1433***	-0.0919***	-0.0267		0.4215	0.1938
	(0.0112)	(0.1702)	(0.0406)	(0.0075)	(0.0280)			
Low HHI	-0.0477***	-0.0203	2.0599***	-0.3008***	-0.0351		0.1769	0***
	(0.0052)	(0.1176)	(0.4555)	(0.0468)	(0.0242)			
High HHI	-0.0076	-0.1873	-0.1425***	-0.0921***	-0.0261	0.0087	0.4217	0.2053
	(0.0113)	(0.1711)	(0.0408)	(0.0075)	(0.0281)	(0.0300)		
Low HHI	-0.0477***	-0.0206	2.0612***	-0.3009***	-0.0351	-0.0017	0.177	0***
	(0.0053)	(0.1180)	(0.4570)	(0.0469)	(0.0243)	(0.0263)		

Panel C: Top 10 Insitutions

	Constant	RQ	HHI_{10}	HHI_{-10}	LIQ	SMB	R^2	$HHI_{10} = HHI_{-10}$
High HHI	-0.0046	-0.1228	-0.1331***	-0.0906***			0.4203	0.1911
	(0.0121)	(0.1812)	(0.0323)	(0.0074)				
Low HHI	-0.0483***	-0.0203	1.4132***	-0.3387***			0.1247	0.0003***
	(0.0055)	(0.1222)	(0.4203)	(0.0631)				
High HHI	-0.0045	-0.1235	-0.1371***	-0.0897***	-0.0248		0.4225	0.1505
	(0.0121)	(0.1812)	(0.0326)	(0.0075)	(0.0276)			
Low HHI	-0.0478***	-0.0423	1.3268**	-0.3288***	-0.0414		0.136	0.0006***
	(0.0055)	(0.1224)	(0.4217)	(0.0631)	(0.0247)			
High HHI	-0.0044	-0.1224	-0.1363***	-0.0898***	-0.0244	0.0058	0.4226	0.1644
	(0.0121)	(0.1817)	(0.0330)	(0.0076)	(0.0277)	(0.0302)		
Low HHI	-0.0478***	-0.0415	1.3264**	-0.3288***	-0.0413	0.0035	0.1361	0.0004***
	(0.0055)	(0.1229)	(0.4227)	(0.0633)	(0.0248)	(0.0269)		

Notes: This table shows results for the estimated regressions in equation (C.3). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. The last column records p-values from testing whether coefficients $HHI_k = HHI_{-k}$, k = 3, 5, 10.

Table E.5: Regression of Conditional Quantile on HHI - First Month Pre-crisis

	Constant		RQ	HHI		LIQ	SMB	R^2
High HHI	-0.0234	*	0.1072	-0.0564	***			0.2309
	(0.0109)		(0.1056)	(0.0071)				
Low HHI	-0.1202	*	-0.6223	-0.0876	***			0.0846
	(0.0571)		(0.7028)	(0.0203)				
High HHI	-0.0231	*	0.1094	-0.0566	***	0.0041		0.231
	(0.0110)		(0.1067)	(0.0072)		(0.0255)		
Low HHI	-0.1225	*	-0.6532	-0.0872	***	-0.0130		0.0875
	(0.0572)		(0.7043)	(0.0203)		(0.0158)		
High HHI	-0.0256	*	0.0897	-0.0548	***	0.0015	-0.0515	0.2432
	(0.0110)		(0.1066)	(0.0072)		(0.0254)	(0.0276)	
Low HHI	-0.1248	*	-0.6825	-0.0868	***	-0.0132	-0.0076	0.0883
	(0.0576)		(0.7088)	(0.0204)		(0.0158)	(0.0174)	

Notes: This table shows results for the estimated regressions in equation (C.4). Quarterly sample starts in 1980Q1 and ends in 2007Q2. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

F Supplementary Granularity Results

In this section we provide supplementary material to the granularity decomposition of returns. In Table F.1 we report parameter estimates of the regression model appearing in equation (12) in the paper. In Figures F.1 through F.3 we report the granularity composition for High/Low HHI portfolios and Top 3 and Top 5 institutional investors. Figures F.4 through F.6 cover the interquartile range, and finally Figures F.8 through F.10 pertain to downside risk.

Table F.1: Granularity Decomposition Regression Parameter Estimates

SIC #	SIC Industry	Model with HHI				Model without HHI			
50	Wholesale Trade	-0.30	0.03	1.30	0.30	-0.25	0.02	1.25	0.02
1	Agriculture, Fishery, Foresty	-0.26	0.13	1.26	0.13	-0.24	0.05	1.24	0.05
70	Services	-0.16	0.01	1.16	0.01	-0.19	0.01	1.19	0.01
15	Construction	-0.14	0.02	1.14	0.02	-0.26	0.03	1.26	0.03
52	Retail Trade	-0.14	0.01	1.14	0.01	-0.13	0.01	1.13	0.01
10	Mining	-0.12	0.01	1.12	0.01	-0.11	0.01	1.11	0.01
20	Manufacturing	-0.11	0.00	1.11	0.00	-0.12	0.00	1.12	0.00
60	Finance, Insurance, Real Estate	-0.08	0.01	1.08	0.01	-0.11	0.01	1.11	0.01
40	Transportation & Public Utilities	-0.06	0.01	1.06	0.01	0.00	0.01	1.00	0.01
91	Public Administration	-0.04	0.03	1.04	0.03	0.12	0.04	0.88	0.04

Notes: This table shows results for regressions in equation (12). Quarterly sample starts in 1982Q1 and ends in 2017Q4. Newey and West (1987) standard errors are in parentheses.

Fig. F.1: Granularity decomposition: Expected Returns High/Low HHI Portfolios

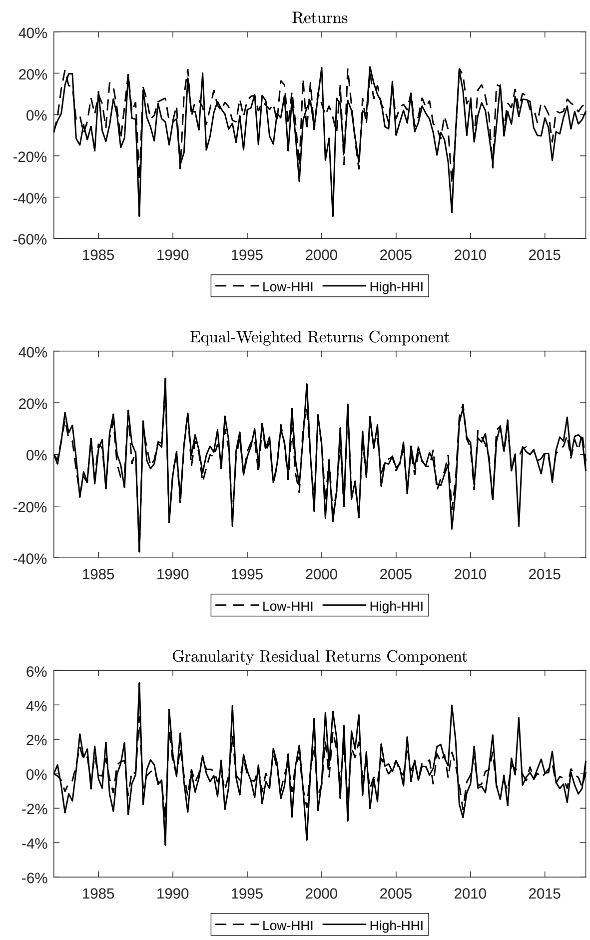


Fig. F.2: Granularity decomposition: Expected Returns High/Low HHI Portfolios Top 3

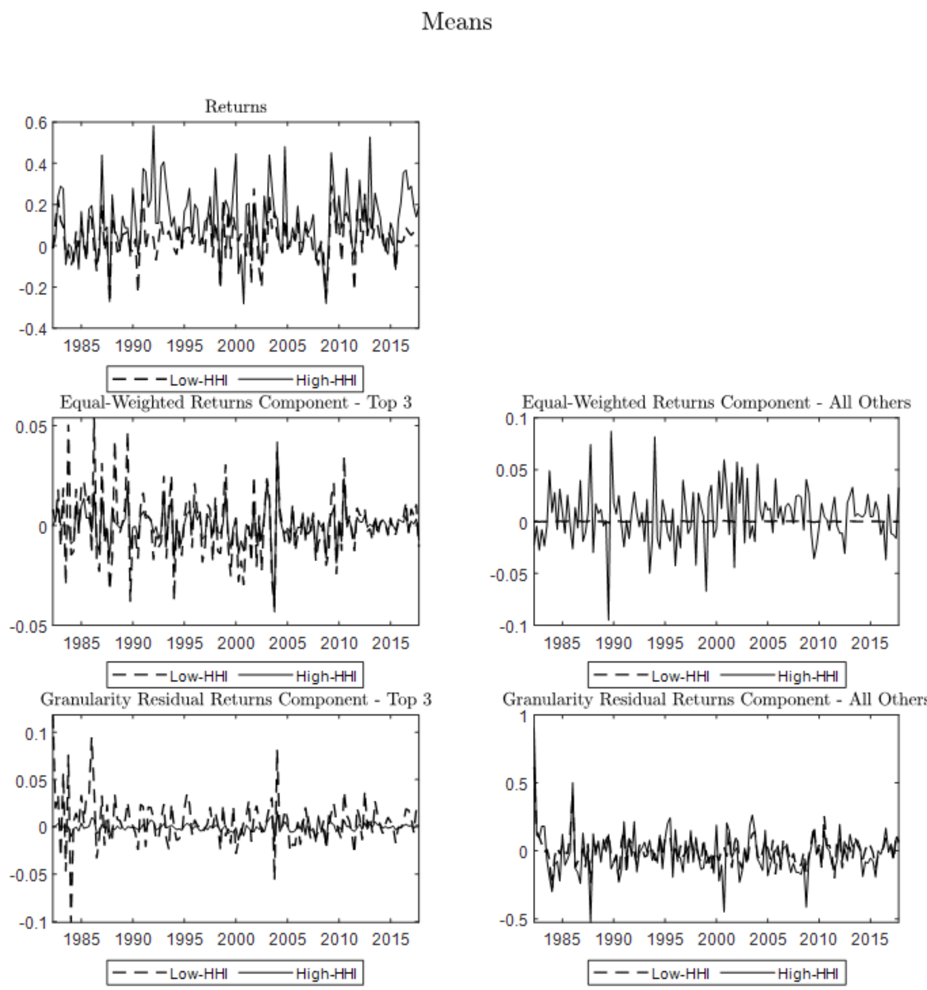


Fig. F.3: Granularity decomposition: Expected Returns High/Low HHI Portfolios Top 5

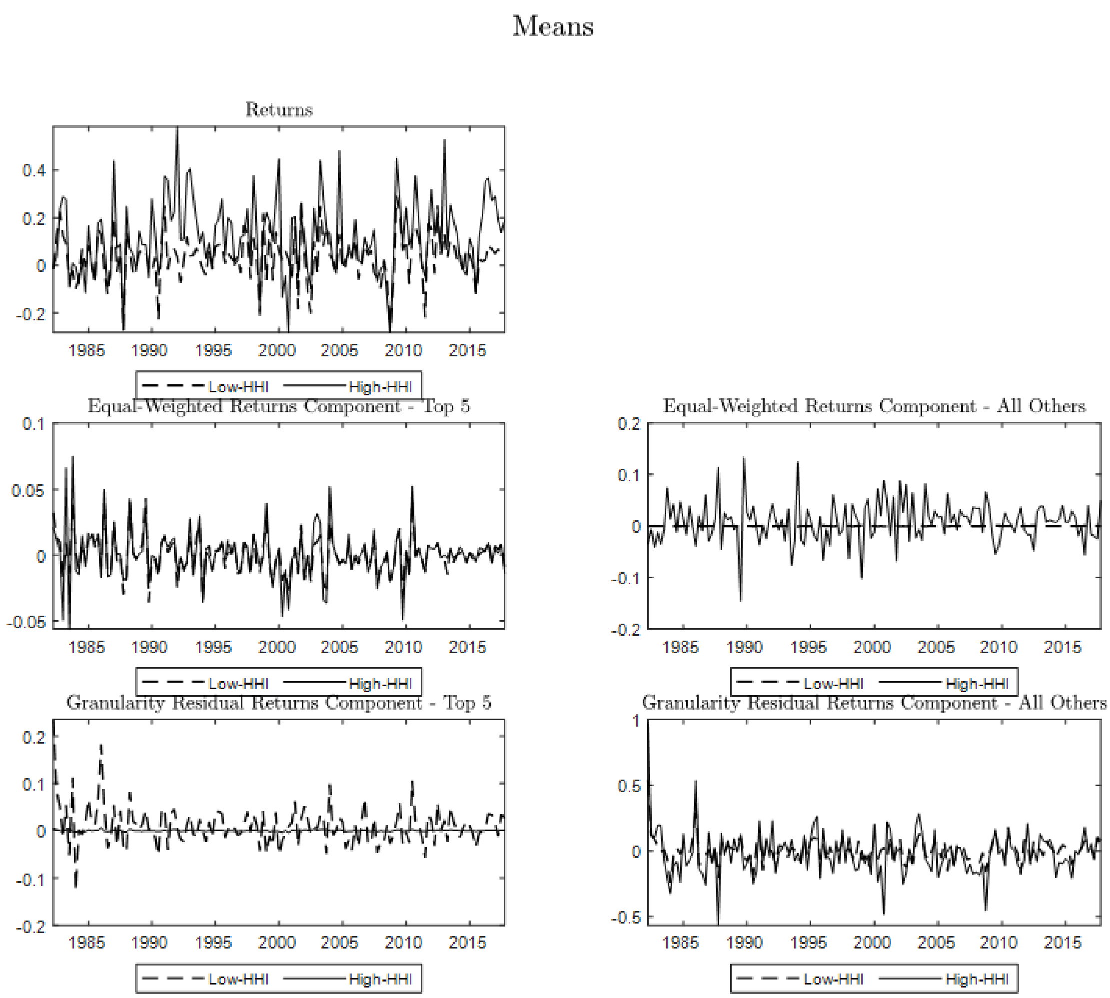


Fig. F.4: Granularity decomposition: Interquantile Range High/Low HHI Portfolios

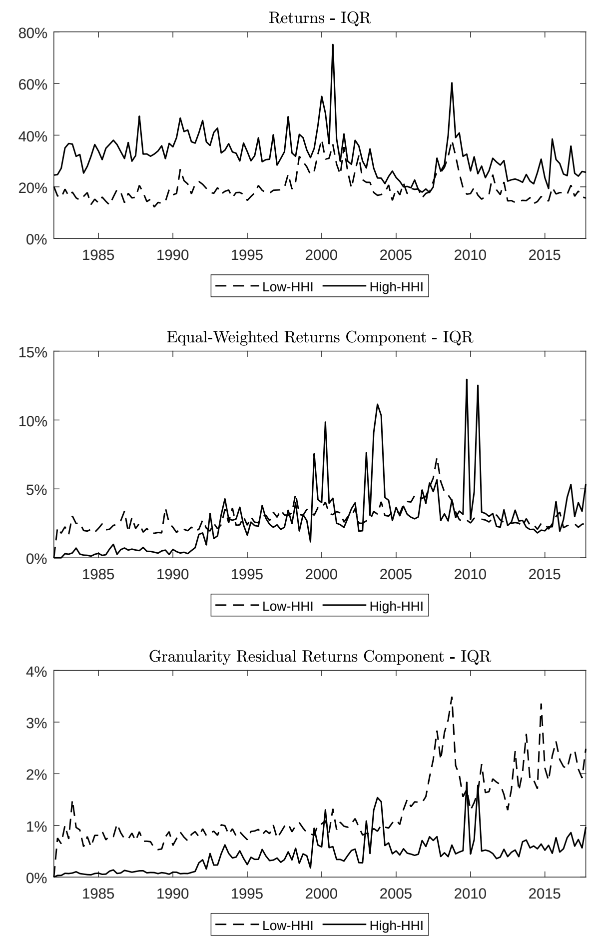


Fig. F.5. Granularity decomposition: Interquantile Range High/Low HHI Portfolios Top 3

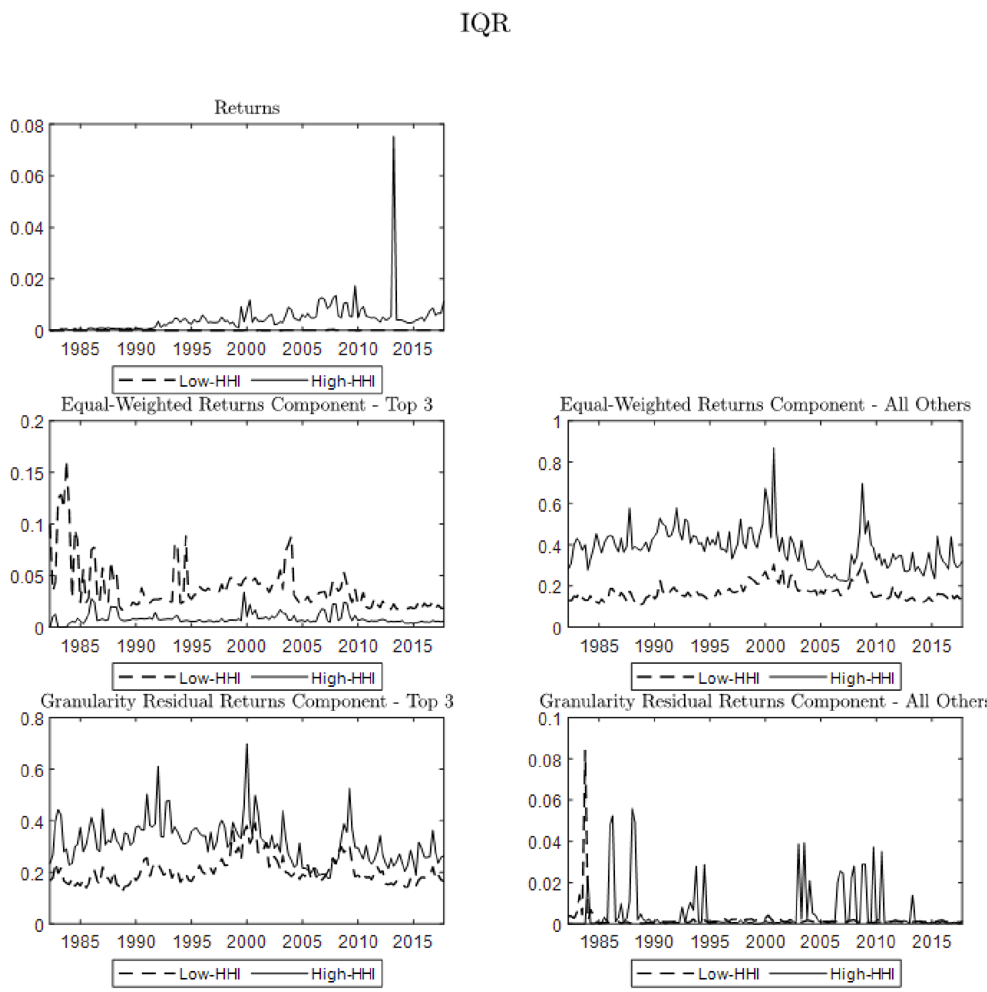


Fig. F.6. Granularity decomposition: Interquantile Range High/Low HHI Portfolios Top 5

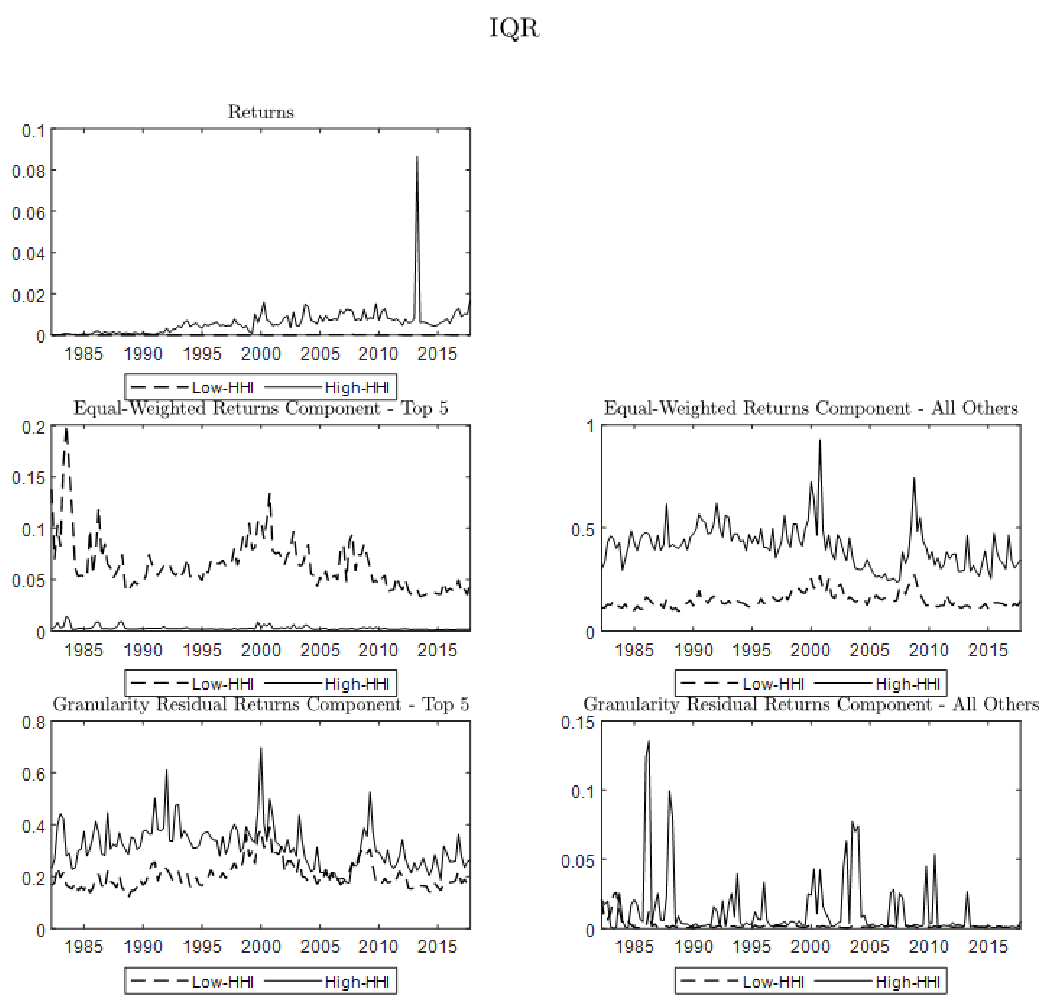


Fig. F.7: Granularity decomposition: Expected Returns High/Low HHI Portfolios Top 10

Means

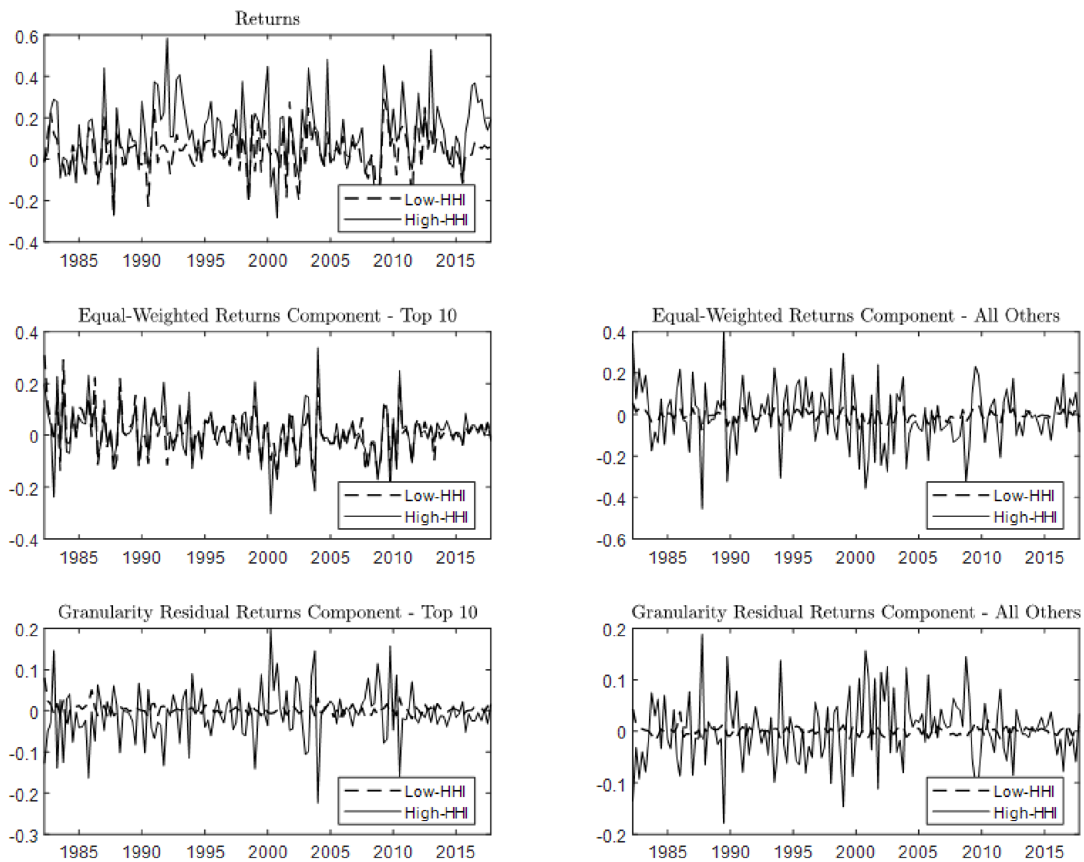


Fig. F.8: Granularity decomposition: Downside Risk High/Low HHI Portfolios

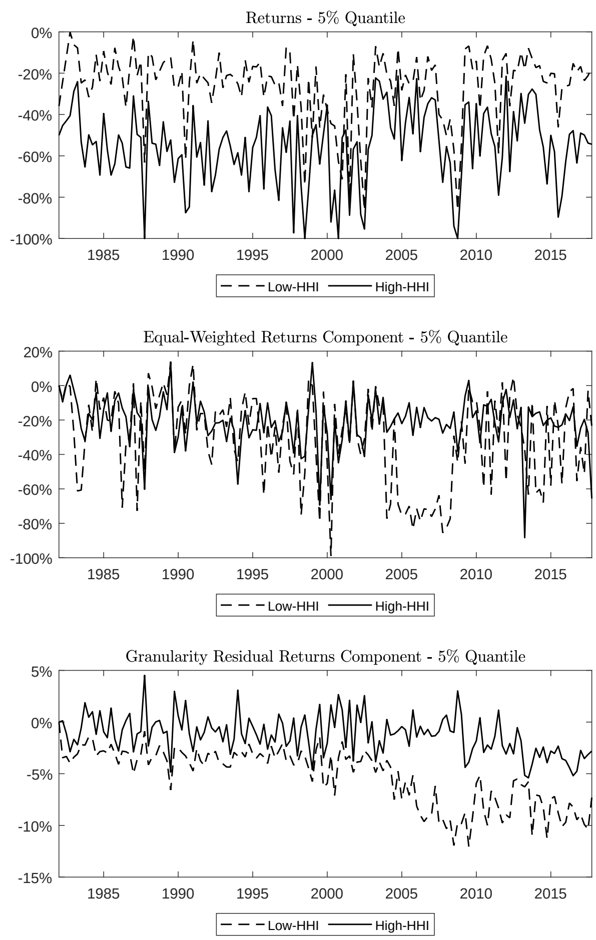


Fig. F.9: Granularity decomposition: Downside Risk High/Low HHI Portfolios Top 3

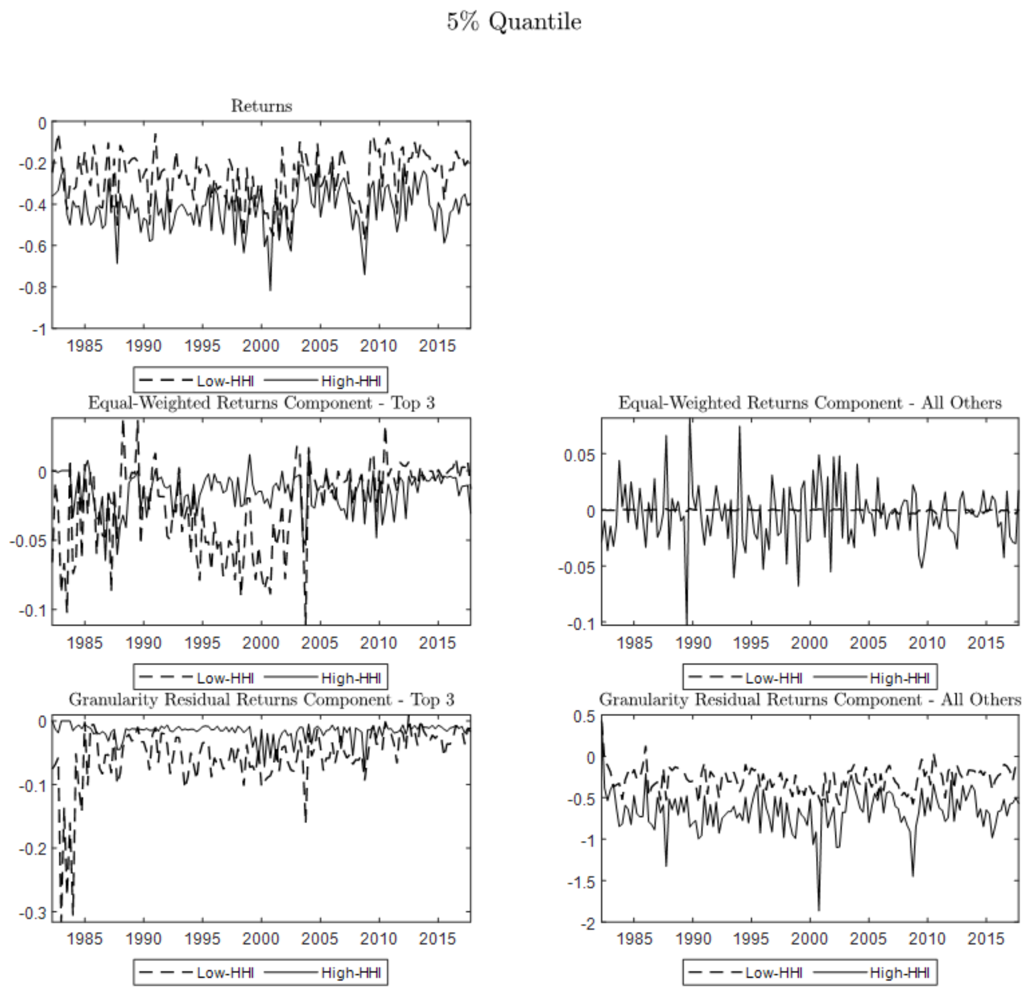


Fig. F.10: Granularity decomposition: Downside Risk High/Low HHI Portfolios Top 5

5% Quantile