Common Asset Holdings and Stock Return Comovement

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Keywords: asset management; institutional investors; return comovement; common ownership
JEL classification: G10; G11; G23

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Abstract

A growing literature highlights the effect of common asset holdings on market dynamics. Focusing on relatively large stocks, Antón and Polk (2014) find that assets with many common investors comove more strongly in the future than otherwise similar stocks. In order to acknowledge the shift in institutional preferences over the last two decades we perform a similar analysis but also include small stocks in our sample. Our main findings are as follows: first, we document a strong increase in both institutional ownership and common asset holdings over the sample period, particularly so for the smallest stocks. Second, raw stock return correlations have also increased strongly over time, while the increase is much more modest for factor model residual correlations. Third, we confirm that common ownership is significantly related to future return correlations for relatively large stocks, but the relationship appears to become less important over time. For relatively small stocks the relationship is often insignificant, but the effect appears to become more important over time. Lastly, we find no evidence that institutional ownership Granger-causes return correlations for the subset of small stocks.

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1 Introduction

A growing literature highlights the effect of investors' common asset holdings on both price and liquidity dynamics. For example, Koch et al. (2016) find that commonality in stock liquidity is likely driven by correlated trading among a given stock's investors. The authors show that stocks with high mutual fund ownership have liquidity comovements that are about twice as large as those for stocks with low mutual fund ownership. Regarding the impact on prices, Antón and Polk (2014) showed that stocks sharing many common investors tend to comove more strongly with each other in the future than otherwise similar stocks, even after controlling for various stock-pair specific characteristics. Similar to Koch et al. (2016), Antón and Polk (2014) explain their finding based on correlated trading strategies among mutual funds. Interestingly, Greenwood and Thesmar (2011) argue that if the investors of mutual funds have correlated trading needs, the stocks that are held by mutual funds can comove even without any portfolio overlap of the funds themselves. For the set of U.S. mutual funds, however, a significant portfolio overlap has been documented (Fricke, 2016), suggesting that common asset holdings are indeed of relevance in the study of market dynamics.

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Note that Antón and Polk (2014) use data from the CRSP Mutual Fund database for the period 1980 - 2008, and restrict their analysis to relatively large stocks only.[1] While this sample selection approach is pervasive in the literature, it is well known that institutional preferences have changed over the last decades. For example, Falkenstein (1996) and Gompers and Metrick (2001) found that institutional investors tend to prefer holding large, liquid stocks. Later on, Bennett et al. (2003) compare institutional investments for the periods 1983-1990 and 1990-1997 and find that investors shifted their preferences towards smaller, riskier securities over this relatively short period. Indeed, we confirm that institutional ownership has increased rather dramatically over the last two decades for most stocks (see Table 1 and Figure 1 below), naturally leading us to ask whether the main results of Antón and Polk (2014) also hold when including smaller stocks to the analysis.[2] This is particularly interesting since nowadays small stocks' level of institutional ownership is comparable to that of large stocks in the 1990s. Hence, we would expect that small stocks' return comovements should be increasingly affected by common asset ownership of institutional investors. This is indeed what we find in the data.

In this paper, we therefore perform a similar analysis as Antón and Polk (2014) for stocks from different size categories, including very small stocks. We use data for the period 1990 - 2014 for the broad set of U.S. institutional investors, and our main findings can be summarized as follows: first, we document a strong increase in both institutional ownership and common asset holdings over the sample period, particularly so for the smallest stocks. Interestingly, the most illiquid stocks (Amihud-ratio) do not display a similar growth in institutional ownership, suggesting that liquidity remains an important characteristic for professional asset managers. Second, we show that raw stock return correlations have also increased strongly over time, while the increase is much more modest when looking at factor-model residual correlations. Third, we confirm that common ownership is significantly related to future return correlations for relatively large stocks, but the relationship appears to become less important over time. For relatively small stocks the relationship is often insignificant, but the effect appears to become more important over time. Lastly, we find no evidence that institutional ownership Granger-causes return correlations for the subset of small stocks. These findings are important because they suggest that smaller stocks, despite being more widely held by professional asset managers, are still relatively illiquid and thus are not generally liquidated in stress periods.

Our paper mainly adds to the literature on common asset holdings. To the best of

[1] More precisely, they state that "*[w]e restrict our analysis to common stocks (share codes 10 and 11) from NYSE, Amex, and NASDAQ whose market capitalizations are above the NYSE median market cap (i.e.,"big" stocks). We choose these screening criteria because common ownership by active managers is not pervasive - small stocks, especially in the beginning of the sample, have little institutional ownership. Limiting the data in this way also keeps the sample relatively homogeneous and ensures that the patterns we find are not just due to small or microcap stocks.*" (See Antón and Polk (2014, p. 1104))

[2] Koch et al. (2016) find that the positive relationship between the mutual fund liquidity beta and mutual fund ownership is strongest for the largest and most liquid stocks. The relationship becomes much weaker for smaller stocks and, in fact, insignificant for the smallest and most illiquid stocks, which are not predominantly held or traded by mutual funds.

our knowledge, our paper is the first to explore the role of common ownership on stock return correlations for relatively small stocks. As such, we also contribute to the literature on institutional preferences by looking at the relationship with stock liquidity (Falkenstein (1996); Gompers and Metrick (2001); Bennett et al. (2003)). In a way, one might argue that, by being more widely held by a larger number of investors, small stocks should have become more liquid. Our findings suggest that the smallest stocks are not necessarily the most illiquid - in fact, we find that the level of institutional ownership has sharply increased for the smallest stocks, but much less so for the most illiquid stocks.

The remainder of this paper is structured as follows: in section 2, we introduce the dataset and describe our main research methodology in section 3. Section 4 contains the main empirical results. In section 5, we study the (Granger-)causality between institutional ownership, return correlation, and liquidity. Finally, section 6 concludes and elaborates on interesting avenues of future work.

2 Data and Summary Statistics

In the following, we briefly introduce the dataset and provide some summary statistics that motivate our analysis.

2.1 Data

In this paper, we combine data from different sources. First, the institutional holdings data come from Thomson Reuters (13F filings) and are updated quarterly. Under Securities Exchange Act Section 3(a)(9) and Section 13(f)(5)(A) all money managers/investment companies with assets under management exceeding $100 million have to submit detailed information on their holdings (number of shares and market valuation) to the SEC on a quarterly basis. The set of institutions includes banks, insurance companies, investment companies, independent investment advisors, and other types of institutions (such as pension funds and university endowments). The reported holdings are at the security level (CUSIPs) and generally constitute equities.[3] We complement the holdings data with the merged CRSP-Compustat files, providing us with daily stock market data, and quarterly accounting data. Lastly, we also have access to the CRSP Mutual Fund database from 2003 onwards and we will use the mutual fund data mainly in order to check the robustness of our results. Our regression analyses below will be performed on monthly data.

In line with the literature, we focus on common stocks (share codes 10 and 11) traded on NASDAQ, NYSE, or AMEX. Our final sample covers the period between January 1990 and December 2014 (300 months) and 13,934 unique stocks for which we have information

[3] Institutions are required to report all equity positions greater than 10,000 shares or $200,000 in market value. The data are not necessarily complete for two additional reasons: first, institutions can request exception from filing their reports in order to prevent disclosure of their trading strategies. Second, institutions only report their longterm positions.

in the merged CRSP-Compustat-Thomson dataset. The final sample contains 1,404,114 stock-month observations.

2.2 Dynamics of Institutional Ownership

Year	Stocks	Pairs	Institutions	InstOwn	FCAP
1990	4,755	11,302,635	954	0.267	0.052
1995	5,942	17,650,711	1,223	0.309	0.058
2000	5,913	17,478,828	1,791	0.333	0.081
2005	4,505	10,145,260	2,263	0.515	0.174
2010	3,791	7,183,945	2,639	0.581	0.244
2014	3,478	6,046,503	3,106	0.560	0.199
Mean	4,839	12,206,711	1,972	0.437	0.132
Median	4,717	11,122,686	1,926	0.425	0.114
SD	998	4,984,672	670	0.124	0.075
Min	3,381	5,713,890	954	0.267	0.038
Max	6,659	22,167,811	3,180	0.615	0.257

Table 1: *Summary Statistics on stocks and institutional investors.* The first part reports the number of stocks, pairs of stocks, number of institutions, the (cross-sectional) average institutional ownership (InstOwn), and our main measure of common investors ($FCAP$). We show statistics for specific dates, and the second part summarizes the statistics over the entire sample period.

Table 1 provides some basic summary statistics of our dataset. For example, we see that the number of financial institutions has tripled over the sample period, but on the other hand, the number of stocks has been decreasing ever since bursting of the dot-com bubble. At the end of our sample period, there were roughly 3,100 reporting institutions and 3,500 stocks (compared with 954 institutions and 4,755 stocks in 1990). As a result, the number of stock pairs is quite large and changes over time: there is a factor 4 between the minimum and maximum number of stock pairs. We also calculate the level of institutional ownership for each stock (InstOwn), which we define as

$$InstOwn_{j,t} = \frac{\sum_i S_{i,j,t}}{ShareOut_{j,t}}, \tag{1}$$

where $S_{i,j,t}$ is the number of shares of stock j held by institution i at time t, and $ShareOut_{j,t}$ is the number of outstanding shares of stock j. In Table 1, we show the cross-sectional average value of InstOwn for different years. We find that it increases during the first half of the dataset and then settles around 0.55 afterwards. In order to explore, to what extent the average InstOwn is representative for different sets of stocks, the top panels of Figure 1 show the average InstOwn for different size quartiles, based on market capitalization ('Q1' are the smallest stocks, and 'Q4' the largest stocks). Not surprisingly, the largest stocks have the highest level of institutional ownership, and the smallest stocks have the lowest level of institutional ownership. In line with the findings of Bennett et al. (2003), however, we find that the level of institutional ownership in small stocks has increased quite rapidly between 2000 and 2005. Hence, institutional preferences indeed appear to have changed over time.[4]

The top right panel of Figure 1 shows evidence of this rapid growth by indexing the InstOwn values in 1990 to 1; with this normalization it becomes clear that the level of institutional ownership for the smallest stocks has increased by a factor of 7 over our sample period. For the largest stocks, this relative increase is much weaker.

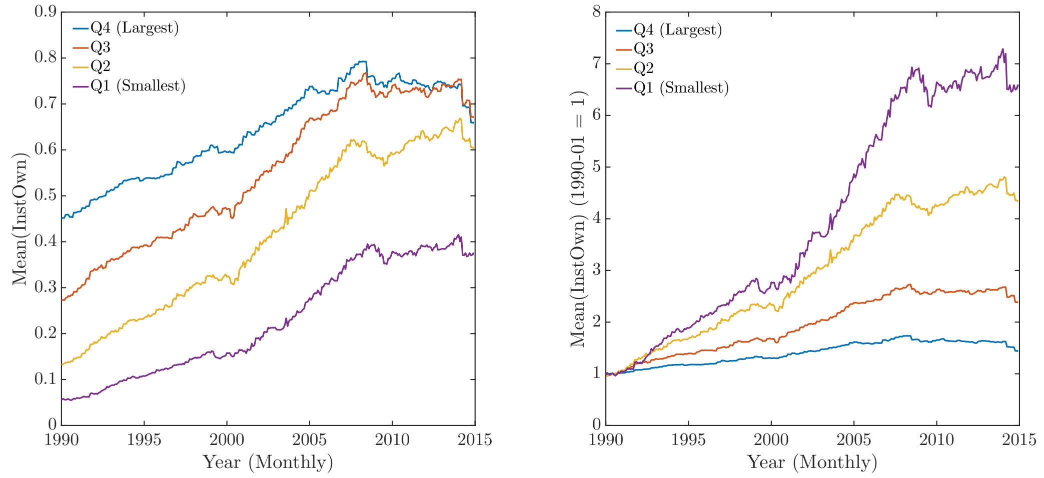
Finally, we define common institutional ownership between stocks j and k, $FCAP_{j,k}$, as the total value of stocks held by all common funds of the two stocks, divided by the total market capitalization of the two stocks

$$FCAP_{j,k,t} = \frac{\sum_{i=1}^{F}(S_{i,j,t}P_{j,t} + S_{i,k,t}P_{k,t})}{ShareOut_{j,t}P_{j,t} + ShareOut_{k,t}P_{k,t}}, \tag{2}$$

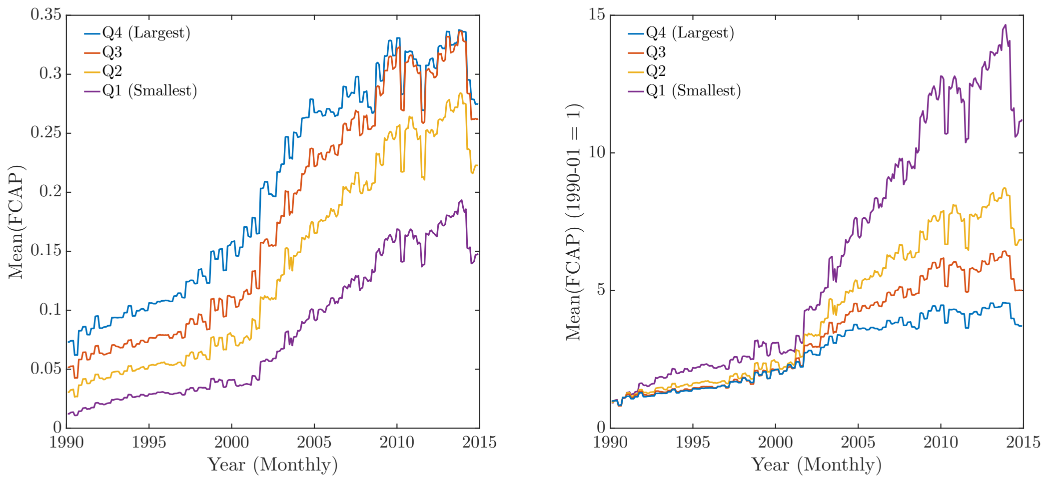
where F is the total number of common funds, and $P_{j,t}$ is the market price of stock j at date t. This will be the main variable of interest in our empirical application below. Interestingly, Table 1 shows that the (cross-sectional) average $FCAP$ appears to increase quite dramatically over our sample period, with values around 0.05 in 1990 and values closer to 0.20 at the end of the sample period. We also explore to what extent these averages are representative for the typical stock: the bottom left panel of Figure 1 shows the typical $FCAP$ values for different size quartiles (again based on market capitalization). In line with the results for InstOwn, we find that common asset ownership appears to be most important for the largest stocks. Interestingly, the average $FCAP$ for the smallest stocks (Q1) at the end of the sample period exceeds that of the largest stocks (Q4) at the beginning of the sample period. In other words, nowadays the smallest stocks have more common investors than large stocks in the early 1990s. Finally, the bottom right panel of Figure 1 normalizes the absolute values in the left panel, illustrating an even more dramatic growth in $FCAP$ for the smallest stocks. Overall, these results confirm that institutional ownership, and thus common asset holdings, has become much more important for relatively small stocks. From the analysis of Antón and Polk (2014) we would expect that small stocks should therefore become much more correlated with other stocks over time, and thus $FCAP$ should be an important explanatory variable for future stock return correlations.

Lastly, Figure 2 is structured similar to Figure 1, but sorts stocks based on their liquidity (using the Amihud-ratio, (Amihud, 2002)). Not surprisingly, more liquid stocks are generally held by more institutional investors. Most of the growth in institutional owner-

[4]Early papers (Gompers and Metrick, 2001; Falkenstein, 1996) show that institutions used to prefer large and very liquid stocks.



(a) InstOwn for different size quartiles (market capitalization).



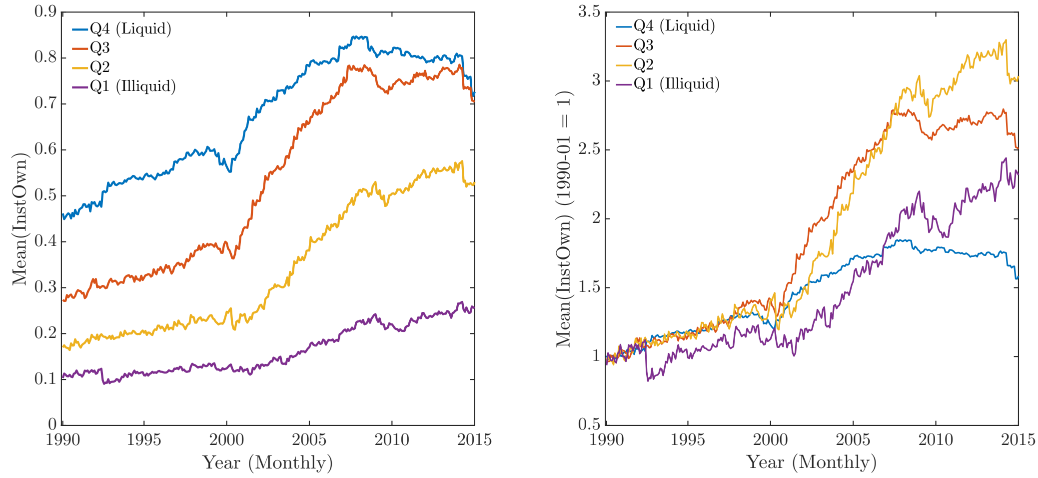
(b) $FCAP$ for different size quartiles (market capitalization).

Figure 1: *Average InstOwn and $FCAP$ by market capitalization quartiles over time.* Top: InstOwn_j is defined as the sum of shares of stock j held by institutional investors relative to the number of outstanding shares. Bottom: $FCAP_{j,k}$ is defined as the relative share of these stocks that are held by investors that hold both of these stocks in their portfolios. The right panels normalize the absolute values for each category such that the initial values in 1990-01 are equal to 1.

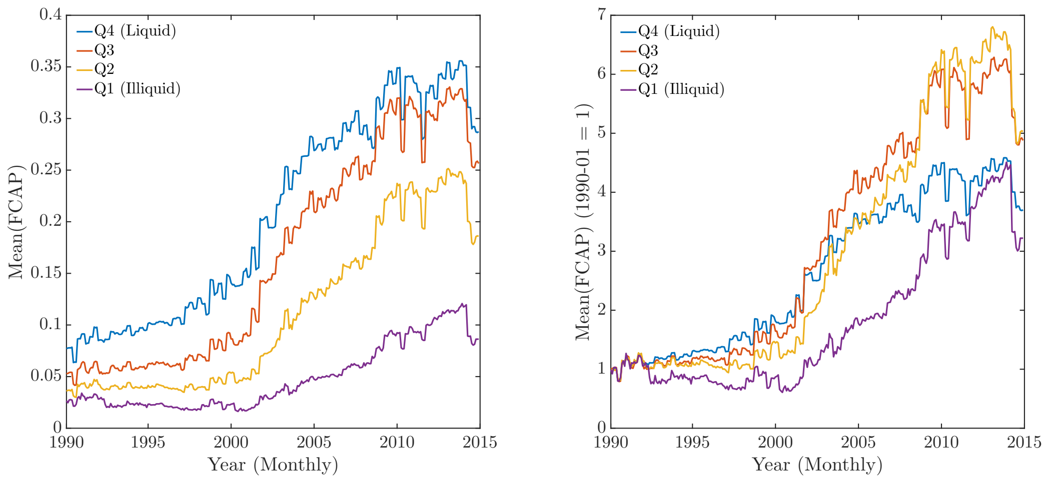
ship, however, was concentrated in the relatively liquid stocks. The change in institutional ownership in both the most liquid and the least liquid stocks has been much less impressive. The result for the latter set of stocks thus suggests that the smallest stocks are not necessarily the most illiquid (see Figure 1).

2.3 Stock Return Correlations

In this paper, we are interested in whether future stock return correlations can be explained via common stock ownership (FCAP). The next section will be dedicated to explaining our methodology in more detail. Before doing so, let us briefly document the dynamics of our



(a) Average InstOwn by illiquidity (Amihud-ratio) quartiles over time.



(b) Average $FCAP$ by illiquidity (Amihud-ratio) quartiles over time.

Figure 2: *Average InstOwn and $FCAP$ by illiquidity quartiles over time.* Top: InstOwn_j is defined as the sum of shares of stock j held by institutional investors relative to the number of outstanding shares. Bottom: $FCAP_{j,k}$ is defined as the relative share of these stocks that are held by investors that hold both of these stocks in their portfolios. The right panels normalize the absolute values for each category such that the initial values in 1990-01 are equal to 1.

dependent variable, namely stock return correlations.

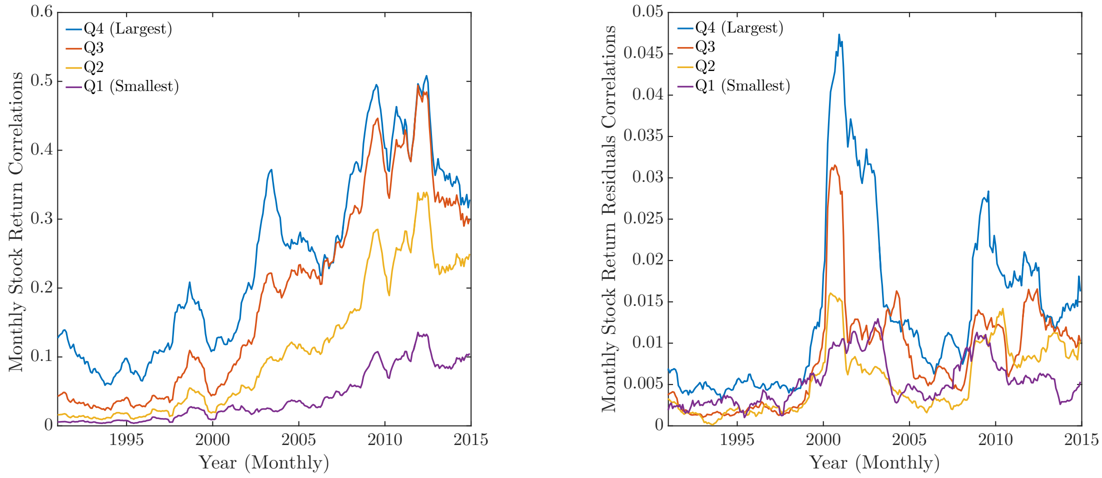
In this regard, Figure 3 shows the average within-category return correlations of stocks from different size quartiles.[5] The left panel shows the results for raw returns, and the right panel shows the same results for the correlations based on 4-factor residuals, ϵ,

$$(r_{j,t} - r_t^f) = \alpha_j + \beta_{j,M}(r_t^M - r_t^f) + \beta_{j,\text{SMB}}\text{SMB}_t + \beta_{j,\text{HML}}\text{HML}_t + \beta_{j,\text{MOM}}\text{MOM}_t + \epsilon_{j,t}, \quad (3)$$

where $(r_t^M - r_t^f)$ denotes the excess return of the market portfolio over the risk-free rate, SMB is the return difference between small and large market capitalization stocks, HML is

[5] In section 4.2, we also explore between-category correlations in more detail.

the return difference between high and low B/M stocks, and MOM is the return difference between stocks with high and low past returns.[6] In both cases, we smoothen the estimates using a 12-month moving average.[7].



(a) Correlations of raw returns.

(b) Correlations of 4-factor residuals.

Figure 3: *12-month moving average of the monthly stock return correlations within stocks of similar size.* Left panel: average correlations based on raw returns. Right panel: average correlations based on 4-factor residuals.

From the raw correlations (left panel) it becomes clear that larger stocks are more correlated among each other compared with smaller stocks. Moreover, we also see that return correlations have increased over our sample period, irrespective of the size of the stocks.[8] On the other hand, when we look at 4-factor residual correlations (right panel), the level of the estimated correlations is much smaller in comparison. As for the raw correlations, the level of comovement among the largest stocks is the largest in general. However, the smallest stocks are not necessarily the least correlated. Furthermore, while the values appear to have increased over time as well for all categories, there is a much weaker time trend in the typical residual correlations. Lastly, we observe some peaks during stress periods for which the correlations can be very large (Pollet and Wilson, 2010) - in fact, for the largest stocks the values during the bursting of the dot-com bubble are almost 10 times as large as the pre-crisis values.

3 Methodology

Let us explain the methodology to test our hypotheses in detail. We follow the approach of Antón and Polk (2014) as closely as possible and are mainly interested in the following

[6]Data source: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library`.

[7]The Appendix shows a similar Figure using 3-factor residuals (excluding the Momentum-factor).

[8]For example, a report by J.P. Morgan from 2010 ("Why We Have a Correlation Bubble", `https://www.cboe.com/institutional/jpmderivativesthemescorrelation.pdf`) argues that high-frequency trading strategies are the most likely source of this increase in correlations.

monthly cross-sectional regressions

$$\rho_{i,j,t+1} = \alpha_t + \beta_{1,t} FCAP^*_{i,j,t} + \sum_{k=2}^{n} \beta_{k,t} CONTROL_{i,j,k,t} + \epsilon_{i,j,t+1}, \tag{4}$$

where $\rho_{i,j,t+1}$ is the daily realized stock return correlations within month $t+1$, α_t is the intercept, and $\beta_{k,t}$ is the estimate of the variable k and $CONTROL_{i,j,k,t}$ is a set of control variables. Hence, we want to explain future stock return comovement based on some fundamental factors and common stock ownership. We use the Fama-MacBeth methodology in everything that follows, and thus show time-averages of the above parameter estimates below. Given the trends in the return correlations documented in the previous section, we use the 4-factor residual correlations in everything that follows. Furthermore, we normalize all explanatory variables to have zero mean and unit standard deviation in order to make the coefficients comparable over time. In the regression tables, all normalized rank-transformed variables are identified with a star ($*$).

3.1 Control Variables

Our set of control variables is as follows: first, we expect stocks from similar industries to comove more strongly with each other. Here we compute the number of consecutive NAICS digits ($NUMNAICS$), beginning with the first digit, that are equal for a given pair. Note that this is a very crude measure of fundamental linkages between firms from different industries, and we suspect that this measure is not sufficient to capture the complex interaction between firms. Ideally we would want to include input-output relationships between different firms, but clearly such data are not easily available. Therefore, we approximate fundamental linkages based on the input-output tables (US Bureau of Economic Analysis, 2015), where we map each stock to one of the 376 industries listed in the USA input-output network. We expect that firms from industries with strong input-output relationships should comove more strongly with each other. Because the input-output network is a directed network for any pair of industries we have two money flows: one from industry a to industry b, and another one from b to a. In the following, we denote IO_1 as the larger value, and IO_2 as the smaller value of the two. Since we have no prior about the functional form that is to be expected, we experimented with different combinations of IO_1 and IO_2. In our regressions below we include the product of these two values, namely $IO_1 \times IO_2$, but we will also control for other combinations.[9] Note that this measure takes complex production chain effects into account (Acemoglu et al., 2012) that is unlikely to be captured by the $NUMNAICS$ control variable.

We also control for other characteristics like $SAMESIZE$ and $SAMEBM$ that are the negative of the absolute difference in percentile ranking for the size and the book-to-market ratio. We also include the absolute difference in financial leverage ratio, noted

[9] We also included additional functional forms of these measures, namely IO_1, IO_2, $(IO_1)^2 \times IO_2$, $IO_1 \times (IO_2)^2$, and $(IO_1)^2 \times (IO_2)^2$.

$DIFFLEV$, and the absolute value of the difference in the two stocks' log share price, $DIFFPRICE$. We also incorporate the past correlation in the two stocks' abnormal trading volume, denoted as $VOLCORR$. Finally, we also include three dummy variables that control for whether the two firms are located in the same states, denoted as $DSTATE$, for stock pairs that are part of the S&P 500 index, denoted as $DINDEX$, for stocks that are listed on the same stock exchange, denoted as $DLISTING$.

In the complete regressions, we will also include different functional forms for some of the control variables. Moreover, we will also include the size of each stock, $SIZE_1$ and $SIZE_2$, and the book-to-market ratio of each stock, BM_1 and BM_2. The label 1 indicates the variable associated to the largest of the two stocks. As mentioned above, we also include different functional forms for the input-output variables.

3.2 Differences to Antón and Polk

Let us briefly summarize the main features that distinguish our analysis from Antón and Polk (2014): first, our main analysis is not restricted to the subset of mutual funds, but includes the broader set of institutional investors. Second, in line with the results from the previous section, we are particularly interested in the results for relatively small stocks for which institutional ownership has increased dramatically over our sample period. Third, the sample of Antón and Polk ends in 2008, just around the time when the global financial crisis of 2008-09 occurred. Our sample includes data up until 2014, thus covering the most recent crisis period which might have an impact on the relationship. Fourth, we add an extra explanatory variable that is linked to the production chain, and thus should be able to capture network effects between firms from different industries. Finally, while we use the same 4-factor model, we also analysed the results for the 3-factor model (excluding the Momentum factor of Carhart, 1997). The results can be found in the Appendix.[10]

4 Empirical Results

4.1 Baseline Specification

The main regression results are summarized in Table 2.[11] The two panels show the results without and with the input-output variables, respectively. As mentioned above, these regressions include all stocks, not only the relatively large ones. In general, we find that the input-output variables are all significant and positive, even when including various other control variables. Thus, the production chain has a large impact on the stock return correlations. With regards to the main variable of interest, we find that $FCAP$ is always

[10]Somewhat surprisingly, the results do depend on whether we use a 3-factor or 4-factor model. This is largely due to the fact that very small stocks appear to load heavily on the Momentum-factor. Thus, residual correlations can be significantly different with or without this factor. In line with Antón and Polk, we thus stick to the 4-factor model in the main text.

[11]The complete Tables with all explanatory variables can be found in the Appendix.

Panel A - Without input-output control variables

Explanatory variables	(1)	(2)	(3)	(4)
Constant	0.00281	−0.00188	−0.00609	−0.00557
	(32.21)	(−8.55)	(−13.59)	(−12.17)
$FCAP^*$	0.00078	0.00033	0.00080	0.00063
	(7.14)	(2.73)	(6.83)	(5.02)
$SAMESIZE^*$		−0.00071	−0.00110	−0.00187
		(−0.86)	(−1.33)	(−0.67)
$NUMNAICS^*$		0.00253	0.00244	0.00242
		(28.51)	(27.49)	(27.20)
Nonlinear size controls	No	Yes	Yes	Yes
Pair characteristic controls	No	No	Yes	Yes
Nonlinear style controls	No	No	No	Yes

Panel B - With input-output control variables

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Constant	0.00139	0.00123	−0.00300	−0.00699	−0.00654
	(11.33)	(10.01)	(−12.30)	(−15.35)	(−13.88)
$FCAP^*$		0.00088	0.00046	0.00090	0.00075
		(8.16)	(3.94)	(7.75)	(6.06)
$IO_1^* \times IO_2^*$	0.00298	0.00300	0.00226	0.00217	0.00221
	(14.52)	(14.63)	(10.82)	(10.38)	(10.50)
$SAMESIZE^*$			−0.00053	−0.00094	−0.00252
			(−0.61)	(−1.10)	(−0.94)
$NUMNAICS^*$			0.00229	0.00222	0.00219
			(25.21)	(24.38)	(24.00)
Nonlinear IO controls	Yes	Yes	Yes	Yes	Yes
Nonlinear size controls	No	No	Yes	Yes	Yes
Pair characteristic controls	No	No	No	Yes	Yes
Nonlinear style controls	No	No	No	No	Yes

Table 2: *Summary of the Fama-MacBeth regressions with and without the input-output control variables.* Panel A shows the regression results for different specifications, excluding the input-output variables. For example, column (1) shows the results when using $FCAP$ as the sole explanatory variable. The other columns include further control variables. Panel B shows similar results when including the input-output controls, with column (5) being the most complete specification. In parenthesis, we indicate the t-statistic associated to each estimate. Table 6 in the Appendix shows the complete regression with a complete list of control variables. Note: $*$ indicates rank-transformed variables (zero mean, unit standard deviation).

positively significant when including all institutions and all stocks, thus confirming the main results of Antón and Polk.

4.2 Subsample Analysis

In order to explore to what extent the above results are stable over time, Table 3 splits the sample into three subsamples. It turns out that the parameter on FCAP is always positively significant in the three subsamples and appears to be very stable over time (the parameter on FCAP is around 0.00075 in all three subsamples). However, Figure 4 illustrates that these averages hide some interesting dynamics. For example, the blue lines show the 12-month moving average of the t-statistic associated with $FCAP$ for our main specification (the left panel corresponds to column (1) in panel A of Table 2; the right panel corresponds to column (5) in panel B of Table 2). Clearly, the results are not constant over time, since there are very large fluctuations, especially so during and after crisis periods: for example, during the dot-com bubble and the 9/11 attacks in 2001, the t-statistic associated to $FCAP$ becomes very large and positive, and then switches to become strongly negative. On the other hand, it is interesting to notice that the effect of the 2008-09 global financial crisis is minor in comparison. Given these strong cyclicalities is it even more remarkable how stable the parameter estimates in Table 3 are.

As a next step, Figure 4 also shows the 12-month moving average t-statistics when running the regressions using (a) only the sample of large stocks (above-median market capitalization), and (b) the set of mutual funds. Regarding (a), the red lines show the t-statistics using the relatively large stocks only; in this case, $FCAP$ is positive and statistically significant, confirming that the results of Antón and Polk (2014) also appear to hold for the larger set of institutional investors. Interestingly, however, the t-statistics appear to be smaller relatively to the baseline specification (blue line) at least for the full model. Lastly, we also show the results based on the CRSP Mutual Fund data, including all stocks (yellow lines). The t-statistic is significantly higher compared to the two previous cases, suggesting that mutual funds are comparably active relative to other asset managers and thus have a stronger impact on the return correlations. This finding is in line with the existing literature, where institutional investors are generally seen as rather inactive long-term investors. However, our results suggest that the common asset holdings of this broader set of professional asset managers also tends to have an impact on future return correlations.

Explanatory variables	(1)	(2)	(3)	(4)	(5)
	First subsample (1990-99)				
Constant	0.00173	0.00091	−0.00063	−0.00419	−0.00213
	(16.66)	(6.24)	(−2.69)	(−7.54)	(−4.16)
$IO_1^* \times IO_2^*$		0.00175	0.00139	0.00137	0.00140
		(7.17)	(5.56)	(5.45)	(5.60)
$FCAP^*$	0.00121	0.00123	0.00054	0.00074	0.00077
	(9.20)	(9.35)	(3.69)	(4.81)	(4.79)
	Second subsample (2000-09)				
Constant	0.00422	0.00235	−0.00365	−0.00850	−0.00888
	(52.93)	(20.07)	(−16.12)	(−20.52)	(−19.91)
$IO_1^* \times IO_2^*$		0.00349	0.00253	0.00239	0.00235
		(18.77)	(13.47)	(12.74)	(12.46)
$FCAP^*$	0.00043	0.00057	0.00047	0.00101	0.00072
	(5.52)	(7.16)	(4.79)	(10.05)	(7.11)
	Third subsample (2010-14)				
Constant	0.00212	−0.00038	−0.00638	−0.00953	−0.01052
	(21.59)	(−2.64)	(−23.72)	(−20.48)	(−20.96)
$IO_1^* \times IO_2^*$		0.00450	0.00344	0.00332	0.00351
		(21.13)	(15.94)	(15.41)	(16.20)
$FCAP^*$	0.00064	0.00079	0.00029	0.00101	0.00075
	(6.31)	(7.81)	(2.71)	(8.95)	(6.47)
Nonlinear IO controls	No	Yes	Yes	Yes	Yes
Nonlinear size controls	No	No	Yes	Yes	Yes
Pair characteristic controls	No	No	No	Yes	Yes
Nonlinear style controls	No	No	No	No	Yes

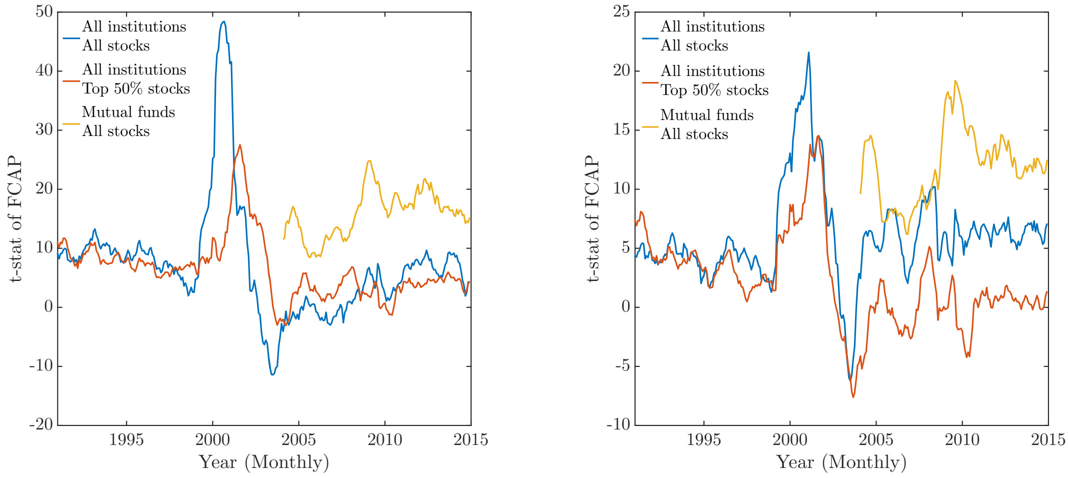
Table 3: *Summary of the regressions for three subsamples.* The periods covered are 1990-99, 2000-09, and 2010-14, respectively. For each period, we perform the same regressions as in Table 6. For the sake of clarity, we only report the estimates of $FCAP$ and $IO_1 \times IO_2$. In parenthesis, we indicate the t-statistic associated to each estimate. Note: $*$ indicates rank-transformed variables (zero mean, unit standard deviation).

4.3 A Closer Look at Different Size Quartiles

The analysis in the previous subsection suggest that small stocks do not necessarily behave dramatically different from large stocks. The next step is to re-run our regressions for the different size quartiles - as before, we separate stocks based on their market capitalization (Q1 denotes the smallest stocks, and Q4 the largest stocks, respectively) to study the dynamics of each category separately.

Therefore, the next step is to run the same regressions from Section 4.1 for stocks of different size quantiles. More precisely, we will run separate regressions as specification (5) panel B of Table 2 for each pair of size quartiles. For example, ‘Q1-Q1’ corresponds to the within-category correlations of the smallest stocks, and ‘Q1-Q4’ corresponds to the between-category correlations between the smallest and largest stocks, respectively. This analysis helps us to fully disentangle the impact of small stocks on the results in the previous section.

The main results are summarized in Table 4. For the sake of brevity, we only report the average parameter estimate and the average t-statistic associated with $FCAP$ (corre-



(a) Only $FCAP$. (b) Full Model.

Figure 4: *12-months moving average of the t-statistic associated to $FCAP$ for each cross-section.* Here we show the values for three different cases: first, the baseline analysis which includes all institutions and all stocks (blue lines). Second, including only relatively large stocks with above-median market capitalization (red lines). Third, using the CRSP Mutual Fund data including all stocks (yellow lines). The left panel shows the t-statistics when $FCAP$ is the only explanatory variable (corresponding to column (1) in panel A of Table 2). The right panel shows the results for the full model including all control variables (corresponding to column (5) in panel B of Table 2).

sponding to column (5) in Panel B of Table 2) over the entire sample and for the three subsamples. Lastly, we also explore whether there are any significant time-trends in the corresponding estimates and t-statistics ('Trend analysis'). For this purpose we run the following simple regressions

$$\text{parameter}_{c,t}^{FCAP} = a_{1,c} + b_{1,c} \times t + \epsilon_{1,t}, \quad (5)$$

$$\text{t-statistic}_{c,t}^{FCAP} = a_{2,c} + b_{2,c} \times t + \epsilon_{2,t}, \quad (6)$$

separately for each pair of categories (here simply denoted as 'c').

Table 4 shows that for the within-category correlations for the largest stocks ('Q4-Q4'), $FCAP$ has a significantly positive impact, however the strength of the relationship is much weaker compared to Antón and Polk (2014). Furthermore, the different subsamples show that the sign of the relationship can change - in this case we see that the typical t-statistics are positive only for the first and second subsample, but negative for the third subsample. Interestingly, we also find a significantly negative trend in the estimates and the t-statistics for the Q4-Q4 case - hence, $FCAP$ appears to become less and less important for explaining future correlations between the set of the largest stocks.

When looking at the results for the relatively small stocks (those involving Q1 and/or Q2), we find positive but insignificant t-statistics in most of the cases. While the values tend to be small, we find a significantly positive trend for the t-statistics involving the

Average parameter estimates for each pair of size categories

	Q1-Q1	Q1-Q2	Q1-Q3	Q1-Q4	Q2-Q2	Q2-Q3	Q2-Q4	Q3-Q3	Q3-Q4	Q4-Q4
Full sample	0.00075 [0.00381]	0.00062 [0.00259]	−0.00014 [0.00285]	0.00007 [0.00312]	0.00007 [0.00288]	−0.00014 [0.00285]	0.00004 [0.00266]	0.00034 [0.00428]	0.00074 [0.00352]	0.00127 [0.00441]
First subsample (1990-1999)	0.00025 [0.00418]	0.00065 [0.00196]	0.00001 [0.00197]	0.00030 [0.00206]	0.00015 [0.00177]	0.00022 [0.00154]	0.00036 [0.00162]	0.00093 [0.00206]	0.00077 [0.00201]	0.00108 [0.00240]
Second subsample (2000-2009)	0.00030 [0.00385]	0.00028 [0.00303]	0.00299 [0.00481]	0.00080 [0.00660]	0.00029 [0.00380]	0.00205 [0.00290]	0.00056 [0.00455]	0.00513 [0.00359]	0.00418 [0.00373]	0.00703 [0.00761]
Third subsample (2010-2014)	0.00094 [0.00352]	0.00062 [0.00294]	−0.00086 [0.00276]	−0.00024 [0.00309]	−0.00018 [0.00337]	−0.00119 [0.00314]	−0.00067 [0.00287]	−0.00144 [0.00473]	0.00032 [0.00411]	0.00114 [0.00451]
Trend analysis										
Intercept	0.00016 (0.36)	0.00027 (0.91)	0.00066 (2.02)	0.00022 (0.61)	0.00021 (0.62)	0.00086 (2.69)	0.00023 (0.76)	0.00169 (3.51)	0.00086 (2.10)	0.00189 (3.70)
Trend	$3.03 \cdot 10^{-6}$ (1.19)	$1.36 \cdot 10^{-6}$ (0.79)	$-5.32 \cdot 10^{-6}$ (−2.82)	$-1.42 \cdot 10^{-6}$ (−0.68)	$-2.17 \cdot 10^{-6}$ (−1.13)	$-8.56 \cdot 10^{-6}$ (−4.63)	$-2.64 \cdot 10^{-6}$ (−1.49)	$-1.16 \cdot 10^{-5}$ (−4.17)	$1.50 \cdot 10^{-7}$ (−0.06)	$-1.61 \cdot 10^{-6}$ (−0.54)
R-squared	0.0047	0.0021	0.0261	0.0015	0.0043	0.0672	0.0074	0.0553	0.0000	0.0010

Average t-statistics for each pair of size categories

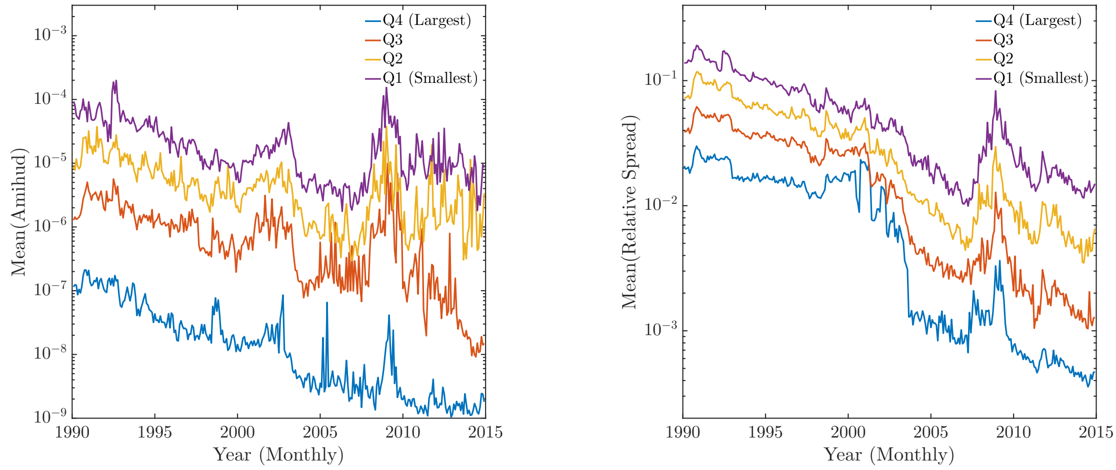
	Q1-Q1	Q1-Q2	Q1-Q3	Q1-Q4	Q2-Q2	Q2-Q3	Q2-Q4	Q3-Q3	Q3-Q4	Q4-Q4
Full sample	0.31 [1.37]	0.42 [1.81]	−0.11 [2.36]	0.05 [2.59]	0.05 [1.90]	−0.17 [3.12]	0.06 [3.02]	0.34 [3.84]	1.27 [4.56]	1.52 [4.69]
First subsample (1990-1999)	0.07 [1.27]	0.36 [1.37]	0.01 [1.77]	0.31 [2.10]	0.14 [1.38]	0.32 [2.19]	0.55 [2.65]	1.37 [2.61]	1.70 [3.92]	1.96 [4.10]
Second subsample (2000-2009)	0.11 [1.51]	0.21 [2.20]	2.64 [4.34]	0.68 [5.86]	0.23 [2.74]	2.48 [3.85]	0.67 [5.31]	5.53 [4.10]	6.51 [5.82]	8.60 [8.83]
Third subsample (2010-2014)	0.40 [1.41]	0.47 [2.05]	−0.59 [2.10]	−0.17 [2.22]	−0.12 [2.10]	−1.16 [3.08]	−0.56 [2.74]	−1.14 [3.58]	0.38 [4.23]	0.84 [3.30]
Trend analysis										
Intercept	0.0071 (0.04)	0.1588 (0.75)	0.5105 (1.88)	0.2632 (0.88)	0.1400 (0.64)	1.1026 (3.15)	0.5942 (1.71)	−0.0121 (4.91)	2.6027 (4.98)	4.0534 (7.66)
Trend	0.0015 (1.63)	0.0010 (0.86)	−0.0038 (−2.43)	−0.0015 (−0.84)	−0.0014 (−1.09)	−0.0093 (−4.58)	−0.0045 (−2.22)	−0.0121 (−4.87)	−0.0083 (−2.75)	−0.0130 (−4.26)
R-squared	0.0088	0.0025	0.0195	0.0024	0.0040	0.0661	0.0163	0.0739	0.0249	0.0577

Table 4: *Summary of the relationship between stock return correlation and $FCAP$ for different combinations of size categories.* The regressions performed here include all the variables listed in column (5) of Table 6 in the Appendix. The first part shows the parameter estimates associated to $FCAP$ when comparing the stock return correlation of stocks in category i with stocks in category j and the second part shows the t-statistic associated to $FCAP$. We also indicate the average estimates and t-statistic within different sub-periods and we study the evolution of each coefficient over time. In parenthesis, we indicate the t-statistic associated to each estimate and in brackets, the standard deviation.

smallest stocks (Q1-Q1). Hence, FCAP tends to become more important for explaining the return correlations among the very small stocks over time.

4.4 Discussion

In summary, these findings show that despite the fact that institutional ownership (and thus $FCAP$) has been strongly increasing for the small stocks over our sample period, we find no evidence that this coincided with a significant increase in return correlations. However, given the positive sign of the relationship between $FCAP$ and 4-factor residual correlations, it appears that pairs of relatively small stocks tend to comove *more* strongly with each other when they share many common investors. While this effect is small, it appears to become more important over time. Antón and Polk (2014) explain their results based on correlated trading strategies, so an obvious question is what is the source of the positive but insignificant relationship for the smaller stocks.



(a) Amihud illiquidity measure

(b) Quoted relative spread

Figure 5: *Evolution of the liquidity of stocks relative to their size.* We compare two measurements for the liquidity (a) the Amihud illiquidity measure and (b) the mean relative spread.

Clearly, liquidity is a likely explanation for this finding: smaller stocks are much less liquid compared to large stocks. In this regard, Figure 5 shows the time dynamics of two illiquidity measures for stocks from different size quartiles: the left panel shows the Amihud-ratio (see Amihud (2002)), and the right panel shows the relative quoted bid-ask spread. (Note that the y-axes is shown on logarithmic scale.) First, we see that size is an important factor for liquidity, and larger stocks are generally more liquid. Second, regarding the time dynamics we see that stocks from all size categories have become much more liquid over the last 25 years. However, it turns out that these dynamics are not necessarily uniform across the different categories: for the largest stocks, we see that the typical Amihud-ratio (relative spread) has decreased by two (one and a half) orders of magnitude, while the values for the smallest stocks have decreased roughly by one order of magnitude in both cases. In other words, nowadays large stocks are even more liquid relative to small stocks than they were 25 years ago.

Coupling these findings with the *FCAP* dynamics and that institutions hold a larger set of illiquid stocks (see Figure 2), it appears reasonable that stressed asset managers are likely to liquidate the most liquid assets first, but refrain from selling small and illiquid stocks. Existing evidence is in line with this interpretation. For example, Nyborg and Östberg (2014) find that, in response to funding shocks, most trading occurs in the set of the most liquid stocks. Relatively illiquid stocks, however, show very little trading activity in these periods. In the next section we provide additional evidence in favor of this explanation.

5 Institutional Ownership, Liquidity, and Correlations

The final step is to analyze the interplay between institutional ownership, stock return correlations, and market liquidity in more detail. Earlier we found that institutional ownership of the smallest stocks has increased significantly over our sample period, and its explanatory power for predicting stock return correlations has increased as well. Hence, we might suspect a causal relationship between these two variables in the sense that higher institutional ownership increases return correlations. Similarly, one might expect that higher institutional ownership improves stocks' liquidity in the sense that there are more potential buyers of a given stock. The effect, however, might also work the other way in the sense that higher liquidity makes stocks more attractive to institutional investors.

Ultimately, the above discussion is about causal effects: does higher institutional ownership lead to higher liquidity? Or does higher liquidity lead to higher institutional ownership? Similarly, does higher institutional ownership increase stocks' return correlations?

In order to answer these questions, ideally we would want using a natural experiment of some kind to properly establish causal effects. However, given that the reported portfolio holdings of institutional investors are at the quarterly level, this seems overly ambitious. Hence, we restrict ourselves to establish Granger-causal relationships in the following (Granger, 1969).

The idea is simple: we wish to estimate the following tri-variate vector autoregressive (VAR) model

$$\begin{pmatrix} \text{InstOwn}_{j,t} \\ \text{Amihud}_{j,t} \\ \text{Correlation}_{j,t} \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} + \begin{pmatrix} b_{1,1} & b_{1,2} & b_{1,3} \\ b_{2,1} & b_{2,2} & b_{2,3} \\ b_{3,1} & b_{3,2} & b_{3,3} \end{pmatrix} \times \begin{pmatrix} \text{InstOwn}_{j,t-1} \\ \text{Amihud}_{j,t-1} \\ \text{Correlation}_{j,t-1} \end{pmatrix} + \begin{pmatrix} e_{j,t} \\ f_{j,t} \\ g_{j,t} \end{pmatrix}, \qquad (7)$$

where the as and bs are the parameters to be estimated, and e, f, and g are independent error terms.[12] Granger-causality is ultimately concerned with the significance of the cross-terms. Broadly speaking, three results can occur: (1) no Granger causality; (2) one-directional Granger causality; and (3) bi- or even tri-directional Granger causality. For instance, if $b_{1,2} = 0$ and $b_{2,1} = 0$ then there is no Granger causality between InstOwn and Amihud. Now, if $b_{1,2} \neq 0$ and $b_{2,1} = 0$ or if $b_{1,2} = 0$ and $b_{2,1} \neq 0$ then there is one-directional Granger causality (from Amihud $\rightarrow$ InstOwn or InstOwn $\rightarrow$ Amihud).

In principle, we can perform the above analysis separately for each stock. It is not clear, however, how we should aggregate the information as the number of stocks is generally on the order of a few thousand. Rather, we will categorize stocks into market capitalisation quartiles (as before), and take averages of the corresponding measures (InstOwn, Amihud, and Correlations) for the analysis. Hence, the results shown below are for the typical stock in each size category.

In order to account for the potential non-stationarity of InstOwn we take the first-

[12] We include additional lags in the regressions, but focus on the case with just one lag, VAR(1), here for illustrative purposes.

Quartiles	Direction	Number of lags 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Q1 (small stocks)	InstOwn→ Correlation	0.386	0.708	0.786	0.518	0.531	0.631	0.665	0.578	0.724	0.770	0.694	0.773	0.582	0.585	0.549	0.634	0.619	0.559
	Amihud → Correlation	0.078	0.251	0.231	0.444	0.571	0.531	0.580	0.666	0.533	0.639	0.685	0.705	0.597	0.631	0.642	0.724	0.659	0.435
	Correlation → InstOwn	0.509	0.676	0.747	0.863	0.689	0.746	0.823	0.865	0.907	0.807	0.783	0.833	0.823	0.658	0.657	0.653	0.673	0.745
	Amihud → InstOwn	0.352	0.382	0.336	0.314	0.196	0.240	0.394	0.382	0.292	0.293	0.359	0.363	0.460	0.657	0.610	0.593	0.654	0.650
	Correlation → Amihud	0.546	0.247	0.268	0.237	0.163	0.317	0.140	0.091	0.123	0.132	0.123	0.212	0.045	0.051	0.085	0.060	0.121	0.195
	InstOwn → Amihud	0.294	0.911	0.980	0.690	0.562	0.544	0.609	0.692	0.568	0.726	0.796	0.819	0.863	0.919	0.952	0.944	0.961	0.968
Q2	InstOwn→ Correlation	0.206	0.284	0.297	0.362	0.314	0.406	0.041	0.036	0.007	0.008	0.012	0.016	0.025	0.019	0.018	0.007	0.007	0.008
	Amihud → Correlation	0.053	0.162	0.083	0.204	0.319	0.304	0.265	0.350	0.279	0.361	0.466	0.444	0.472	0.404	0.419	0.579	0.720	0.762
	Correlation → InstOwn	0.039	0.047	0.237	0.340	0.403	0.215	0.140	0.157	0.195	0.080	0.116	0.140	0.182	0.184	0.193	0.259	0.285	0.384
	Amihud → InstOwn	0.589	0.742	0.913	0.961	0.901	0.922	0.882	0.903	0.553	0.524	0.514	0.637	0.769	0.802	0.732	0.735	0.779	0.816
	Correlation → Amihud	0.267	0.805	0.673	0.596	0.695	0.584	0.249	0.357	0.507	0.613	0.571	0.682	0.797	0.480	0.367	0.446	0.512	0.646
	InstOwn → Amihud	0.302	0.269	0.423	0.577	0.649	0.156	0.166	0.179	0.144	0.208	0.189	0.249	0.326	0.292	0.271	0.134	0.181	0.253
Q3	InstOwn→ Correlation	0.864	0.750	0.547	0.474	0.411	0.531	0.594	0.669	0.507	0.645	0.299	0.302	0.459	0.438	0.470	0.552	0.565	0.482
	Amihud → Correlation	0.009	0.046	0.125	0.189	0.374	0.511	0.632	0.670	0.494	0.630	0.697	0.797	0.847	0.875	0.916	0.943	0.961	0.969
	Correlation → InstOwn	0.058	0.119	0.014	0.035	0.077	0.052	0.082	0.124	0.026	0.031	0.032	0.065	0.096	0.158	0.171	0.192	0.239	0.139
	Amihud → InstOwn	0.137	0.284	0.272	0.397	0.304	0.349	0.352	0.346	0.406	0.347	0.153	0.228	0.264	0.257	0.379	0.445	0.477	0.604
	Correlation → Amihud	0.144	0.454	0.803	0.862	0.684	0.502	0.524	0.545	0.519	0.472	0.506	0.573	0.375	0.476	0.534	0.599	0.644	0.650
	InstOwn → Amihud	0.150	0.128	0.190	0.225	0.171	0.323	0.263	0.292	0.189	0.006	0.007	0.003	0.001	0.001	0.001	0.003	0.005	0.007
Q4 (large stocks)	InstOwn→ Correlation	0.061	0.079	0.031	0.052	0.091	0.151	0.051	0.074	0.090	0.116	0.086	0.111	0.114	0.083	0.108	0.117	0.159	0.200
	Amihud → Correlation	0.013	0.165	0.349	0.498	0.656	0.786	0.885	0.874	0.904	0.934	0.947	0.971	0.982	0.967	0.986	0.909	0.929	0.927
	Correlation → InstOwn	0.737	0.805	0.954	0.637	0.595	0.652	0.767	0.857	0.422	0.466	0.582	0.615	0.651	0.657	0.516	0.569	0.664	0.725
	Amihud → InstOwn	0.167	0.189	0.412	0.601	0.715	0.706	0.802	0.825	0.589	0.655	0.753	0.837	0.888	0.928	0.965	0.960	0.965	0.980
	Correlation → Amihud	0.959	0.990	0.995	0.897	0.951	0.960	0.933	0.933	0.934	0.955	0.954	0.851	0.883	0.928	0.935	0.952	0.951	0.974
	InstOwn → Amihud	0.359	0.466	0.680	0.793	0.725	0.834	0.935	0.955	0.958	0.969	0.978	0.931	0.952	0.947	0.912	0.923	0.963	0.957

Table 5: *Granger causality analysis between institutional ownership, correlations of stock return residuals and Amihud.* The arrows in the second column indicate the direction of the Granger causality. The values indicate for each lag and each test the probability to reject the null hypothesis of no causality. For each test, the shade cells represent the best model according to the likelihood-ratio test. We use the first order difference of the institutional ownership because of the non-stationarity. Amihud is the Amihud (2002) illiquidity-measure.

difference in everything that follows. Correlations are, as before, the 4-factor residual correlations and are the average correlations within each category.[13]

We use a symmetric number of lags meaning that the three variables have the same number of lags in the regressions. To find the best number of lags, we perform a statistical test: we first set the maximum number of lags equal to 18 months. The model with 18 lags is viewed as the unrestricted model. On the other hand, a model with fewer lags is considered as a restricted version of the previous model. Then, we use the LR-ratio test[14] to check whether the restrictions have significantly degraded the fit of the model. The best model is then the one with the minimal number of terms without any significant loss in the explanatory power of the unrestricted model.[15]

Table 5 summarizes the main results. For each quartile, the best number of lags is indicated by the cells in grey, which are the specifications of interest. The Table shows the p-values for each of the potential Granger-causal relationships. We first note that for Q1, Q3, and Q4 the optimal number of lags is around 12 months, while for Q2 it is 18 months. We find that InstOwn Granger-causes Correlations only for stocks in Q2. In other words, for the smallest stocks, higher institutional ownership does not increase those stocks correlations with other stocks. Interestingly, we find that for the smallest stocks (Q1) Correlations Granger-cause Amihud but we do not find any additional significant relationship for these stocks. In particular, we find no evidence that higher InstOwn improves these stocks liquidity. For relatively large stocks (Q3 and Q4), the results are not uniform either: for example, for Q3 we find that Correlations Granger-cause InstOwn, and InstOwn Granger-causes Amihud. For the largest stocks, similar to the stocks in Q2, we find that InstOwn Granger-causes Correlations, but this relationship is not significant at the 10% level.

Overall, these results are in line with the findings in previous sections: the liquidity of small stocks has not increased dramatically despite the rise in institutional ownership in these stocks. On the other hand, we find that institutional ownership Granger-causes correlations only for stocks in Q2 and is borderline significant for the largest stocks.

6 Conclusion

In this paper, we explored to what extent common asset holdings are useful in predicting future return correlations for stocks of different sizes. In particular, we analyzed the results

[13]Table 8 in the Appendix shows the results when using return correlations instead. Because these correlations appear to be non-stationary (see Figure 3), we use the first-difference in this case. The qualitative results are very similar to the ones presented here for stocks in Q4. For Q1, Q2, and Q3 there are some differences.

[14]The likelihood ratio statistic is the chi-squared distributed test statistic and is given by $LR = (T - c)(\log|\Sigma_r| - \log|\Sigma_u|)$ with T the number of observations, c is a degrees of freedom correction factor, and $|\Sigma_r|$, $|\Sigma_u|$ denote the determinant of the error covariance matrices from the restricted and unrestricted models (LeSage, 1999).

[15]To accept the restricted model, the threshold for the marginal probability is set to 1%. Increasing the marginal probability to 5% does not change the results.

for very small stocks for which a shift in institutional preferences has been documented.

Our main results were as follows: first, we document a strong increase in both institutional ownership and common asset holdings over the sample period, particularly so for the smallest stocks. Second, raw stock return correlations have also increased strongly over time, while the increase is much more modest for factor model residual correlations. Third, we confirm that common ownership is significantly related to future return correlations for relatively large stocks, but the relationship appears to become less important over time. For relatively small stocks the relationship is often insignificant, but the effect appears to become more important over time. Lastly, we find no evidence that institutional ownership Granger-causes return correlations for the subset of small stocks.

Overall, these findings suggest that the relationship between common asset holdings and return correlations is not necessarily uniform for stocks of different size

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A Tables

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Constant	0.00281	0.00123	−0.00300	−0.00699	−0.00654
	(32.21)	(10.01)	(−12.30)	(−15.35)	(−13.88)
$IO_1^* \times IO_2^*$		0.00300	0.00226	0.00217	0.00221
		(18.31)	(13.87)	(13.22)	(12.09)
$FCAP^*$	0.00078	0.00088	0.00046	0.00090	0.00075
	(7.14)	(8.16)	(3.94)	(7.75)	(6.06)
$SAMESIZE^*$			−0.00053	−0.00094	−0.00252
			(−0.61)	(−1.10)	(−0.94)
$SAMEBM^*$			0.00147	0.00153	0.00319
			(1.90)	(1.96)	(1.38)
$NUMNAICS^*$			0.00229	0.00222	0.00219
			(25.21)	(24.38)	(24.00)
$SIZE_1^*$			−0.00452	−0.00290	−0.00283
			(−28.95)	(−16.02)	(−15.36)
$SIZE_2^*$			0.00263	0.00105	0.00107
			(15.87)	(5.92)	(6.05)
$SIZE_1^* \times SIZE_2^*$			−0.00415	−0.00474	−0.00480
			(−14.00)	(−15.58)	(−15.84)
$DIFFLEV^*$				−0.00050	−0.00079
				(−5.14)	(−7.56)
$DIFFPRICE^*$				−0.00188	−0.00185
				(−17.90)	(−17.50)
$DINDEX$				0.00207	0.00198
				(5.53)	(5.59)
$DSTATE$				0.00412	0.00410
				(10.80)	(10.81)
$DLISTING$				0.00230	0.00230
				(12.19)	(12.26)
$VOLCORR^*$				0.00375	0.00379
				(10.46)	(10.59)
IO_1^*		0.00033	0.00085	0.00082	0.00082
		(1.98)	(4.71)	(4.54)	(4.49)
IO_2^*		0.00037	0.00004	0.00005	0.00004
		(2.21)	(0.00)	(0.10)	(0.05)
$IO_1^{*2} \times IO_2^*$		0.00119	0.00091	0.00085	0.00085
		(6.71)	(5.07)	(4.71)	(4.72)
$IO_1^* \times IO_2^{*2}$		0.00118	0.00078	0.00069	0.00070
		(8.34)	(5.45)	(4.79)	(4.85)
$IO_1^{*2} \times IO_2^{*2}$		0.00051	0.00038	0.00033	0.00033
		(6.95)	(5.09)	(4.50)	(4.47)
$SAMESIZE^{*2}$			0.00085	0.00065	0.00203
			(8.27)	(6.70)	(1.06)
$SAMESIZE^{*3}$			−0.00049	−0.00030	0.00118
			(−3.98)	(−2.51)	(1.17)

Continued on next page

Table 6 – *Continued from previous page*

Explanatory variables	(1)	(2)	(3)	(4)	(5)
$SIZE_1^{*2}$			0.00407	0.00514	0.00514
			(20.66)	(22.36)	(22.49)
$SIZE_2^{*2}$			0.00291	0.00340	0.00341
			(14.05)	(16.01)	(16.08)
$SIZE_1^{*2} \times SIZE_2^{*2}$			−0.00071	−0.00081	−0.00080
			(−5.44)	(−6.06)	(−6.03)
$SIZE_1^{*} \times SIZE_2^{*2}$			−0.00005	−0.00044	−0.00046
			(−0.70)	(2.00)	(−2.12)
$SIZE_1^{*2} \times SIZE_2^{*}$			0.00112	0.00168	0.00169
			(4.82)	(6.51)	(6.61)
$SAMEBM^{*2}$					−0.00144
					(−0.59)
$SAMEBM^{*3}$					−0.00152
					(−1.31)
BM_1^{*}					0.02150
					(−5.59)
BM_2^{*}					−0.00529
					(9.26)
$BM_1^{*} \times BM_2^{*}$					−0.08882
					(−2.03)
BM_1^{*2}					0.24179
					(2.52)
BM_2^{*2}					−0.08384
					(−1.12)
$BM_1^{*} \times BM_2^{*2}$					−1.31108
					(0.51)
$BM_1^{*2} \times BM_2^{*}$					1.30231
					(−0.71)
$BM_1^{*2} \times BM_2^{*2}$					0.00001
					(2.92)
R^2	0.00004	0.00022	0.00102	0.00126	0.00140

Table 6: *Complete regression table with the input-output variables.* In parenthesis, we indicate the t-statistic associated to each estimate. Note: $*$ indicates rank-transformed variables (zero mean, unit standard deviation).

Explanatory variables	(1)	(2)	(3)	(4)
Constant	0.00281	−0.00188	−0.00609	−0.00557
	(32.21)	(−8.55)	(−13.59)	(−12.17)
$FCAP^*$	0.00078	0.00033	0.00080	0.00063
	(7.14)	(2.73)	(6.83)	(5.02)
$SAMESIZE^*$		−0.00071	−0.00110	−0.00187
		(−0.86)	(−1.33)	(−0.67)
$SAMEBM^*$		0.00183	0.00184	0.00272
		(2.40)	(2.40)	(1.20)
$NUMNAICS^*$		0.00253	0.00244	0.00242
		(28.51)	(27.49)	(27.20)
$SIZE_1^*$		−0.00445	−0.00275	−0.00262
		(−28.56)	(−15.27)	(−14.32)
$SIZE_2^*$		0.00270	0.00103	0.00113
		(16.36)	(5.83)	(6.37)
$SIZE_1^* x SIZE_2^*$		−0.00413	−0.00476	−0.00483
		(−13.95)	(−15.65)	(−15.93)
$DIFFLEV^*$			−0.00046	−0.00077
			(−4.85)	(−7.40)
$DIFFPRICE^*$			−0.00199	−0.00194
			(−18.94)	(−18.30)
$DINDEX$			0.00217	0.00212
			(6.05)	(6.00)
$DSTATE$			0.00403	0.00405
			(10.55)	(10.65)
$DLISTING$			0.00241	0.00242
			(12.79)	(12.95)
$VOLCORR^*$			0.00378	0.00382
			(10.54)	(10.66)
$SAMESIZE^{*2}$		0.00088	0.00068	0.00172
		(8.55)	(6.90)	(0.98)
$SAMESIZE^{*3}$		−0.00051	−0.00032	0.00065
		(−4.19)	(−2.64)	(0.80)
$SIZE_1^{*2}$		0.00409	0.00520	0.00523
		(20.77)	(22.67)	(22.85)
$SIZE_2^{*2}$		0.00292	0.00344	0.00344
		(14.09)	(16.16)	(16.17)
$SIZE_1^{*2} x SIZE_2^{*2}$		−0.00071	−0.00081	−0.00081
		(−5.47)	(−6.08)	(−6.04)
$SIZE_1^* x SIZE_2^{*2}$		−0.00005	−0.00047	−0.00048
		(−0.68)	(−2.08)	(−2.18)
$SIZE_1^{*2} x SIZE_2^*$		0.00111	0.00171	0.00172
		(4.81)	(6.63)	(6.76)
$SAMEBM^{*2}$				−0.00108
				(−0.46)
$SAMEBM^{*3}$				−0.00100

Continued on next page

Table 7 – *Continued from previous page*

Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**
				(−0.95)
BM_1^*				0.02283
				(−4.76)
BM_2^*				−0.00502
				(10.90)
$BM_1^* x BM_2^*$				−0.09458
				(−2.23)
BM_1^{*2}				0.25105
				(2.79)
BM_2^{*2}				−0.08540
				(−1.27)
$BM_1^* x BM_2^{*2}$				−1.34393
				(0.31)
$BM_1^{*2} x BM_2^*$				1.33493
				(−0.50)
$BM_1^{*2} x BM_2^{*2}$				0.00001
				(2.53)
R^2	0.00004	0.00089	0.00113	0.00128

Table 7: *Complete regression table without input-output control variables.* In parenthesis, we indicate the t-statistic associated to each estimate. Note: $*$ indicates rank-transformed variables (zero mean, unit standard deviation).

Quartiles	Direction	Number of lags																	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Q1 (small stocks)	InstOwn→ Correlation	0.485	0.897	0.925	0.212	0.194	0.101	0.057	0.086	0.008	0.003	0.004	0.002	0.002	0.003	0.006	0.002	0.005	0.009
	Amihud → Correlation	0.278	0.517	0.641	0.642	0.817	0.846	0.812	0.865	0.782	0.789	0.893	0.914	0.896	0.910	0.840	0.726	0.740	0.763
	Correlation → InstOwn	0.111	0.217	0.439	0.460	0.577	0.530	0.626	0.726	0.744	0.694	0.783	0.127	0.237	0.293	0.330	0.283	0.274	0.370
	Amihud → InstOwn	0.393	0.448	0.406	0.377	0.286	0.310	0.414	0.354	0.280	0.415	0.508	0.410	0.523	0.603	0.676	0.723	0.830	0.840
	Correlation → Amihud	0.166	0.233	0.381	0.190	0.164	0.143	0.242	0.134	0.117	0.173	0.186	0.234	0.254	0.199	0.242	0.324	0.455	0.265
	InstOwn → Amihud	0.367	0.956	0.994	0.760	0.544	0.502	0.644	0.737	0.475	0.628	0.707	0.772	0.746	0.760	0.803	0.810	0.855	0.872
Q2	InstOwn→ Correlation	0.380	0.728	0.854	0.918	0.910	0.966	0.929	0.953	0.901	0.737	0.574	0.609	0.735	0.776	0.856	0.590	0.587	0.460
	Amihud → Correlation	0.127	0.232	0.185	0.242	0.386	0.373	0.472	0.597	0.451	0.444	0.143	0.121	0.056	0.072	0.091	0.087	0.131	0.179
	Correlation → InstOwn	0.320	0.613	0.744	0.662	0.837	0.736	0.302	0.059	0.025	0.047	0.069	0.006	0.010	0.015	0.030	0.048	0.075	0.045
	Amihud → InstOwn	0.892	0.980	0.963	0.980	0.949	0.932	0.919	0.934	0.626	0.697	0.743	0.841	0.898	0.897	0.921	0.911	0.942	0.956
	Correlation → Amihud	0.259	0.003	0.005	0.009	0.012	0.016	0.043	0.067	0.067	0.162	0.081	0.124	0.132	0.159	0.178	0.165	0.076	0.130
	InstOwn → Amihud	0.380	0.244	0.448	0.600	0.700	0.147	0.098	0.070	0.058	0.082	0.076	0.103	0.138	0.205	0.232	0.084	0.107	0.174
Q3	InstOwn→ Correlation	0.594	0.863	0.653	0.586	0.698	0.615	0.011	0.024	0.011	0.007	0.024	0.013	0.021	0.010	0.019	0.009	0.006	0.012
	Amihud → Correlation	0.498	0.359	0.155	0.191	0.109	0.098	0.128	0.122	0.130	0.040	0.072	0.019	0.016	0.022	0.033	0.036	0.038	0.069
	Correlation → InstOwn	0.658	0.928	0.972	0.977	0.975	0.879	0.772	0.195	0.267	0.209	0.200	0.115	0.162	0.116	0.059	0.086	0.072	0.067
	Amihud → InstOwn	0.067	0.170	0.283	0.419	0.275	0.318	0.383	0.243	0.301	0.195	0.106	0.198	0.280	0.158	0.273	0.330	0.368	0.385
	Correlation → Amihud	0.908	0.724	0.979	0.978	0.553	0.182	0.161	0.191	0.229	0.430	0.296	0.231	0.265	0.418	0.430	0.481	0.522	0.620
	InstOwn → Amihud	0.219	0.159	0.217	0.274	0.234	0.314	0.255	0.267	0.213	0.025	0.021	0.016	0.003	0.003	0.008	0.014	0.017	0.026
Q4 (large stocks)	InstOwn→ Correlation	0.168	0.323	0.556	0.280	0.273	0.321	0.108	0.104	0.114	0.112	0.090	0.162	0.155	0.076	0.106	0.136	0.186	0.143
	Amihud → Correlation	0.453	0.653	0.738	0.653	0.874	0.932	0.912	0.921	0.959	0.973	0.867	0.885	0.904	0.905	0.913	0.927	0.935	0.919
	Correlation → InstOwn	0.493	0.539	0.566	0.731	0.723	0.490	0.526	0.217	0.200	0.246	0.318	0.388	0.464	0.530	0.276	0.154	0.134	0.183
	Amihud → InstOwn	0.119	0.191	0.401	0.529	0.682	0.779	0.859	0.826	0.723	0.813	0.845	0.921	0.917	0.965	0.984	0.966	0.964	0.978
	Correlation → Amihud	0.459	0.406	0.249	0.356	0.502	0.695	0.917	0.943	0.980	0.987	0.977	0.988	0.936	0.962	0.941	0.953	0.928	0.960
	InstOwn → Amihud	0.395	0.448	0.667	0.745	0.779	0.874	0.970	0.952	0.966	0.985	0.995	0.979	0.986	0.984	0.938	0.960	0.955	0.957

Table 8: *Granger causality analysis between institutional ownership, correlations of the raw stock return and liquidity.* The arrows in the second column indicate the direction of the Granger causality. The values indicate for each lag and each test the probability to reject the null hypothesis of no causality. For each test, the shade cells represent the best model according to the likelihood-ratio test. We use the first order difference of the institutional ownership and of the raw stock return correlations because of the non-stationarity. Amihud is the Amihud (2002) illiquidity-measure.

B Results derived using the 3-factor model instead of the 4-factor model

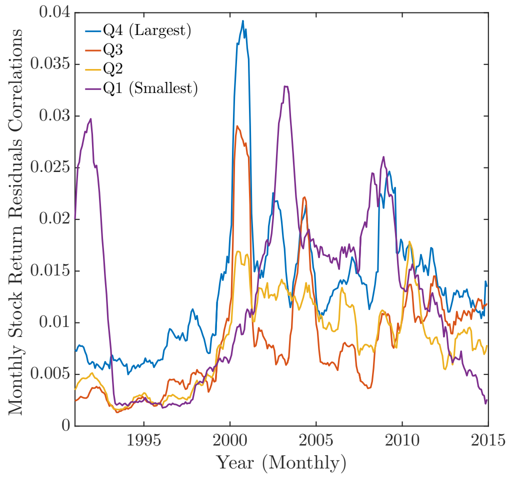
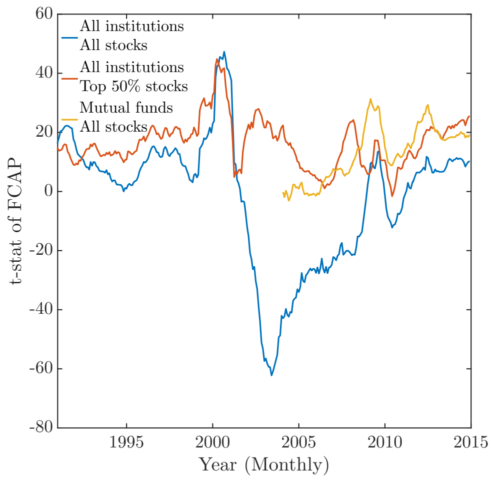
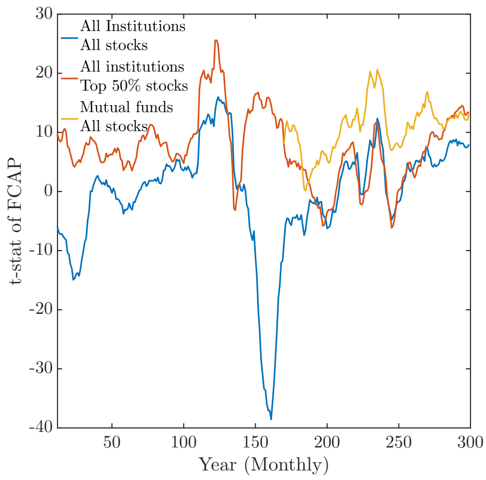


Figure 6: *12-months moving average of the monthly stock return residuals correlations within stocks of similar size based on the 3-factor model.*



(a) Only $FCAP$.



(b) Full Model.

Figure 7: *12-months moving average of the evolution of the t-statistic associated to $FCAP$ for each cross-section based on the 3-factor model.* Here we show the values for three different cases: first, the baseline analysis which includes all institutions and all stocks (blue lines). Second, including only relatively large stocks with above-median market capitalization (red lines). Third, using the CRSP Mutual Fund data including all stocks (yellow lines). The left panel shows the t-statistics when $FCAP$ is the only explanatory variable (corresponding to column (1) in panel A of Table 2). The right panel shows the results for the full model including all control variables (corresponding to column (5) in panel B of Table 2).

Panel A - Without input-output control variables

Explanatory variables	(1)	(2)	(3)	(4)
Constant	0.00506	−0.00054	−0.00490	−2.26320
	(72.78)	(−0.94)	(−12.26)	(−11.19)
*FCAP**	−0.00016	−0.00021	0.00013	−0.00011
	(−1.42)	(−1.18)	(1.43)	(−1.42)
*SAMESIZE**		−0.00121	−0.00136	−0.00098
		(−2.32)	(−2.47)	(−1.60)
*NUMNAICS**		0.00246	0.00240	0.00236
		(32.55)	(31.72)	(31.11)
Nonlinear size controls	No	Yes	Yes	Yes
Pair characteristic controls	No	No	Yes	Yes
Nonlinear style controls	No	No	No	Yes

Panel B - With input-output control variables

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Constant	0.00336	0.00337	−0.00179	−0.00590	7.11102
	(33.92)	(34.00)	(−6.69)	(−14.62)	(−13.27)
*FCAP**		−0.00005	−0.00008	0.00024	−0.00001
		(0.12)	(−1.00)	(2.60)	(−0.26)
$IO_1^* \times IO_2^*$	0.00313	0.00311	0.00237	0.00227	0.00210
	(18.46)	(18.31)	(13.87)	(13.22)	(12.07)
*SAMESIZE**			−0.00102	−0.00120	−0.00227
			(−1.90)	(−2.10)	(−1.14)
*NUMNAICS**			0.00219	0.00214	0.00210
			(28.32)	(27.66)	(27.15)
Nonlinear IO controls	Yes	Yes	Yes	Yes	Yes
Nonlinear size controls	No	No	Yes	Yes	Yes
Pair characteristic controls	No	No	No	Yes	Yes
Nonlinear style controls	No	No	No	No	Yes

Table 9: *Summary of the 3-factor Fama-MacBeth regressions with and without the input-output control variables.* Panel A shows the regression results for different specifications, excluding the input-output variables. For example, column (1) shows the results when using $FCAP$ as the sole explanatory variable. The other columns include further control variables. Panel B shows similar results when including the input-output controls, with column (5) being the most complete specification. In parenthesis, we indicate the t-statistic associated to each estimate. Note: $*$ indicates rank-transformed variables (zero mean, unit standard deviation).

Average estimates for each pair of size categories

	Q1-Q1	Q1-Q2	Q1-Q3	Q1-Q4	Q2-Q2	Q2-Q3	Q2-Q4	Q3-Q3	Q3-Q4	Q4-Q4
Full sample	0.00004 [0.00265]	−0.00008 [0.00246]	−0.00046 [0.00246]	−0.00081 [0.00240]	−0.00023 [0.00308]	−0.00017 [0.00315]	−0.00047 [0.00278]	0.00011 [0.00456]	0.00023 [0.00378]	0.00037 [0.00441]
First subsample (1990-1999)	−0.00026 [0.00161]	−0.00017 [0.00103]	−0.00029 [0.00123]	−0.00035 [0.00139]	−0.00025 [0.00090]	0.00001 [0.00081]	−0.00023 [0.00095]	0.00025 [0.00107]	0.00034 [0.00106]	0.00087 [0.00205]
Second subsample (2000-2009)	0.00029 [0.00320]	−0.00031 [0.00284]	−0.00083 [0.00319]	−0.00102 [0.00271]	−0.00072 [0.00305]	−0.00100 [0.00330]	−0.00146 [0.00333]	−0.00058 [0.00494]	−0.00048 [0.00421]	0.00023 [0.00522]
Third subsample (2010-2014)	0.00041 [0.00281]	0.00049 [0.00289]	−0.00046 [0.00247]	−0.00149 [0.00278]	0.00077 [0.00420]	0.00054 [0.00413]	−0.00060 [0.00305]	0.00019 [0.00599]	0.00081 [0.00470]	0.00005 [0.00520]
Trend analysis										
Intercept	−0.00107 (−3.54)	−0.00093 (−3.27)	−0.00074 (−2.61)	−0.00045 (−1.62)	−0.00059 (−1.64)	−0.00027 (−0.74)	−0.00048 (−1.48)	0.00026 (0.48)	0.00000 (0.00)	0.00081 (1.57)
Trend	$5.93 \cdot 10^{-6}$ (3.39)	$3.95 \cdot 10^{-6}$ (2.42)	$-1.35 \cdot 10^{-6}$ (−0.82)	$-4.34 \cdot 10^{-6}$ (−2.73)	$1.88 \cdot 10^{-6}$ (0.91)	$-2.86 \cdot 10^{-6}$ (−1.36)	$-1.60 \cdot 10^{-6}$ (−0.86)	$-3.37 \cdot 10^{-6}$ (−1.10)	$0.60 \cdot 10^{-6}$ (0.24)	$-2.68 \cdot 10^{-6}$ (−0.91)
R-squared	0.0373	0.0193	0.0023	0.0245	0.0028	0.0062	0.0025	0.0041	0.0002	0.0028

Average t-statistics for each pair of size categories

	Q1-Q1	Q1-Q2	Q1-Q3	Q1-Q4	Q2-Q2	Q2-Q3	Q2-Q4	Q3-Q3	Q3-Q4	Q4-Q4
Full sample	0.05 [2.69]	−0.28 [3.67]	−0.80 [3.80]	−1.42 [3.46]	−0.42 [3.02]	−0.37 [4.19]	−1.00 [3.91]	0.21 [4.38]	0.45 [5.16]	0.49 [4.52]
First subsample (1990-1999)	−0.20 [1.73]	−0.47 [2.78]	−0.67 [3.60]	−0.97 [3.68]	−0.63 [2.64]	0.12 [3.50]	−0.74 [3.85]	0.72 [3.60]	1.54 [4.81]	1.66 [5.06]
Second subsample (2000-2009)	0.20 [3.68]	−0.45 [4.54]	−1.30 [4.20]	−1.97 [3.41]	−0.88 [3.42]	−1.61 [4.42]	−2.14 [3.87]	−0.91 [5.04]	−1.38 [5.89]	−0.40 [4.71]
Third subsample (2010-2014)	0.30 [1.73]	0.53 [2.59]	−0.42 [1.80]	−1.13 [2.25]	0.53 [2.72]	0.71 [3.72]	−0.39 [2.70]	0.27 [3.35]	1.41 [2.98]	0.40 [2.37]
Trend analysis										
Intercept	−2.1203 (−5.73)	−2.4535 (−5.49)	−2.8506 (−5.88)	−2.4470 (−5.23)	−1.0349 (−3.01)	−0.6618 (−1.39)	−0.7827 (−1.72)	0.9421 (1.95)	1.4478 (2.41)	2.3141 (4.20)
Trend	0.0106 (4.97)	0.0103 (4.00)	0.0079 (2.83)	0.0048 (1.77)	0.0038 (1.89)	−0.0016 (−0.60)	−0.0012 (−0.44)	−0.0062 (−2.24)	−0.0073 (−2.11)	−0.0104 (−3.27)
R-squared	0.0768	0.0511	0.0262	0.0105	0.0119	0.0012	0.0007	0.0166	0.0148	0.0348

Table 10: *Summary of the relationship between stock return correlation and $FCAP$ for different combinations of size categories based on the 3-factor model.* The regressions performed here include all the variables listed in column 5 in Table 6 in the Appendix. The first part shows the estimates associated to $FCAP$ when comparing the stock return correlation of stocks in category i with stocks in category j and the second part shows the t-statistic associated to $FCAP$. We also indicate the average estimates and t-statistic within different sub-periods and we study the evolution of each coefficient over time. In parenthesis, we indicate the t-statistic associated to each estimate and in brackets, the standard deviation.

Quartiles	Direction	Number of lags																	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Q1 (small stocks)	InstOwn→ Correlation	0.944	0.115	0.226	0.144	0.199	0.286	0.384	0.374	0.390	0.399	0.281	0.243	0.031	0.026	0.029	0.022	0.045	0.050
	Amihud → Correlation	0.461	0.719	0.579	0.771	0.715	0.784	0.866	0.904	0.942	0.959	0.760	0.690	0.381	0.455	0.637	0.619	0.671	0.643
	Correlation → InstOwn	0.427	0.619	0.844	0.491	0.600	0.772	0.853	0.606	0.651	0.718	0.763	0.543	0.589	0.536	0.628	0.771	0.660	0.686
	Amihud → InstOwn	0.364	0.399	0.396	0.311	0.243	0.344	0.493	0.408	0.231	0.266	0.266	0.196	0.276	0.416	0.437	0.500	0.605	0.609
	Correlation → Amihud	0.184	0.228	0.039	0.082	0.028	0.056	0.062	0.034	0.086	0.127	0.125	0.094	0.124	0.113	0.112	0.103	0.039	0.029
	InstOwn → Amihud	0.331	0.931	0.974	0.666	0.543	0.570	0.679	0.815	0.796	0.894	0.928	0.946	0.948	0.979	0.982	0.977	0.979	0.972
Q2	InstOwn→ Correlation	0.313	0.684	0.857	0.732	0.839	0.418	0.428	0.508	0.198	0.193	0.185	0.276	0.194	0.216	0.194	0.060	0.082	0.048
	Amihud → Correlation	0.008	0.061	0.061	0.154	0.251	0.409	0.460	0.537	0.477	0.456	0.495	0.743	0.513	0.181	0.239	0.289	0.210	0.141
	Correlation → InstOwn	0.766	0.570	0.455	0.458	0.616	0.115	0.115	0.157	0.061	0.067	0.087	0.119	0.085	0.067	0.095	0.122	0.122	0.159
	Amihud → InstOwn	0.993	0.975	0.933	0.970	0.901	0.866	0.786	0.824	0.361	0.378	0.353	0.426	0.500	0.617	0.636	0.651	0.769	0.786
	Correlation → Amihud	0.097	0.727	0.880	0.896	0.928	0.773	0.863	0.939	0.964	0.977	0.980	0.986	0.987	0.964	0.969	0.984	0.974	0.970
	InstOwn → Amihud	0.314	0.282	0.466	0.641	0.753	0.170	0.184	0.142	0.103	0.139	0.114	0.145	0.201	0.196	0.252	0.092	0.159	0.197
Q3	InstOwn→ Correlation	0.882	0.618	0.748	0.673	0.502	0.563	0.667	0.478	0.219	0.272	0.112	0.107	0.209	0.234	0.260	0.289	0.370	0.349
	Amihud → Correlation	0.029	0.060	0.126	0.142	0.272	0.424	0.523	0.532	0.338	0.383	0.514	0.564	0.624	0.672	0.733	0.822	0.873	0.891
	Correlation → InstOwn	0.097	0.218	0.004	0.010	0.025	0.020	0.024	0.044	0.028	0.038	0.066	0.078	0.108	0.159	0.163	0.227	0.282	0.154
	Amihud → InstOwn	0.154	0.299	0.217	0.357	0.310	0.297	0.254	0.274	0.308	0.224	0.128	0.189	0.219	0.197	0.304	0.332	0.381	0.481
	Correlation → Amihud	0.031	0.198	0.491	0.491	0.584	0.549	0.516	0.602	0.668	0.720	0.731	0.758	0.514	0.612	0.658	0.715	0.775	0.731
	InstOwn → Amihud	0.136	0.109	0.153	0.223	0.191	0.325	0.238	0.223	0.177	0.009	0.009	0.005	0.001	0.001	0.003	0.005	0.010	0.014
Q4 (large stocks)	InstOwn→ Correlation	0.294	0.050	0.066	0.117	0.165	0.235	0.138	0.161	0.102	0.112	0.086	0.100	0.128	0.096	0.093	0.061	0.056	0.073
	Amihud → Correlation	0.003	0.065	0.158	0.268	0.406	0.568	0.636	0.448	0.565	0.487	0.576	0.662	0.702	0.720	0.829	0.532	0.484	0.528
	Correlation → InstOwn	0.874	0.984	0.968	0.947	0.584	0.669	0.646	0.750	0.495	0.533	0.656	0.523	0.614	0.618	0.617	0.709	0.774	0.829
	Amihud → InstOwn	0.153	0.197	0.398	0.589	0.653	0.628	0.672	0.741	0.483	0.541	0.658	0.702	0.766	0.814	0.892	0.920	0.934	0.961
	Correlation → Amihud	0.927	0.989	0.994	0.862	0.914	0.909	0.916	0.926	0.877	0.879	0.892	0.906	0.919	0.940	0.958	0.957	0.987	0.989
	InstOwn → Amihud	0.359	0.463	0.678	0.783	0.697	0.792	0.912	0.934	0.921	0.932	0.947	0.906	0.929	0.910	0.863	0.878	0.905	0.885

Table 11: *Granger causality analysis between institutional ownership, correlations of stock return residuals based on the 3-factor model and Amihud.* The arrows in the second column indicate the direction of the Granger causality. The values indicate for each lag and each test the probability to reject the null hypothesis of no causality. For each test, the shade cells represent the best model according to the likelihood-ratio test. We use the first order difference of the institutional ownership because of the non-stationarity. Amihud is the Amihud (2002) illiquidity-measure.