Institutional Herding:
A Study On the Similarity Between Institutional Investment Fund Equity Portfolios

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ABSTRACT

KRAMER, ALEX Herding Among Institutional Investment Funds. Department of Economics, Union College.

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This study examines the overlap in portfolios of institutional investment funds. I use the 13F filings of over 3,300 distinct funds of long equity positions. Portfolio overlap is calculated as a cosine similarity between two funds' portfolios, which is the product of overlapping portfolio weights, and is bound between zero and one. Of academic importance are the characteristics that predict the extent to which an institutional investment fund herds. In particular, I ask whether small funds copy large funds, foreign copy domestic, and if funds holding a small number of equity positions copy funds with a large number of positions. First, I focus on overlap in portfolios of pairs of funds in the same quarter. I find that overlap is statistically significantly greater in pairs of funds with similar AUM levels, whereas overlap is not driven by fund location. Second, I calculate the overlap across different quarters to show which funds follow and which funds lead. I find that intertemporal similarity is almost exclusively driven by contemporaneous similarity. From a practical perspective, identifying which funds tend to lead rather than follow could be a proxy for the independence of their investment research. In future research I plan to investigate whether the leadership effect predicts future returns.

1. Introduction:

Aggregate assets under management of publicly disclosed holdings of institutional investment funds reached a record $22.6 trillion at the end of the second quarter of 2015. As regulation is favoring transparency in the investment industry, institutional investors' investment strategies have caught the public's attention and questions are being raised about the effects institutional investors are having on securities markets.

Institutional herding raises a number of concerns, especially with the industry's massive growth. The potential for herding to play a role in destabilizing market conditions is particularly concerning. In response, numerous papers investigate this including Lakonishok, Shleifer, and Vishny (1992), Wermers (1999), Gompers and Metrick (2001), Brunnermeier and Nagel (2004), Dasgupta, Prat, and Verardo (2008), Puckett and Yan (2008), Jiao and Ye (2014), and Reca, Sias, and Turtle (2014). These concerns are echoed by the press and by hedge fund managers as well. For instance, an article in the Wall Street Journal states that, "hedge funds are crowding into more of the same trades these days, amplifying market swings during crises and unnerving investors. Such trading has stoked market jitters in recent months and helped to diminish the impact of corporate fundamentals on stock-market movements" (January 14, 2011). Daniel Loeb—head of Third Point LLC, which manages roughly $17 billion—wrote in his June 2010 investor letter, "Please note that we will no longer discuss investments made prior to our public 13F filings. We have found that discussing our ideas may result in 'piling on' by other hedge funds who may subsequently sell at inopportune times resulting in greater hedge fund concentration and volatility, which is not in the interest of our investors." Increased transparency due to 13F filings facilitates herding and their interpretations have generated contentious debate.

Robust literature has evolved to better understand the existence and effects of herding among all institutional investors, as well as specific subsets of institutions. For example, Lakonishok, Shleifer, and Vishny (1992) study a sample of pension funds, whereas Grinblatt, Titman, and Wermers (1995) and Wermers (1999) study a large sample of mutual funds and find evidence of herding in small stocks. Brunnermeier and Nagel (2004), Griffin and Xu (2007), and Reca, Sias, and Turtle (2014) study hedge funds by analyzing their holdings. In the past fifteen years, a general consensus has formed that herding exists and that it is significant. However, consensus on the impact of such herding on securities prices is less conclusive. Of particular interest are the implications of institutional herding on how information is impounded in the market and its effect on securities prices. The primary purpose of this paper is to investigate whether institutional investment funds herd and to identify which funds copy others. Additionally, I am going to investigate the correlation between different fund characteristics and which drive similarity the most. The rest of this paper is organized as follows. The next section reviews the relevant literature on herding among institutional investment funds. Section 3 discusses the data that are used and how I formed my sample. Section 4 explains the methodology I use to calculate similarity. I test the similarity between pairs of funds contemporaneously and then intertemporally for my entire sample and then for specific subsamples in Section 5. I conclude in Section 6.

2. Literature Review:

There is now vast literature on institutional herding. Research on herding among institutional investors dates back to Kraus and Stoll (1972), who examine parallel trading, which is the same as herding, but they find no evidence of herding. Most of the early herding literature was focused on subsets of institutional investors, such as mutual funds (e.g. Grinblatt, Titman, and Wermers, 1995; Wermers, 1999) and pension funds (Lakonishok, Shleifer, and Vishny, 1992), and provide little empirical evidence for institutional herding. However, Grinblatt, Titman, and Wermers (1995) and Wermers (1999) find evidence of herding in small stocks.

2.1 Measures of Herding

As the Lakonishok, Shleifer, and Vishny (hereafter LSV) "herding measure" relies on portfolio data and is easily adaptable, it has been widely used in empirical literature concerned with herding (see Grinblatt, Titman, and Wermers, 1995; Wermers, 1999; Wylie. 2005; Puckett and Yan 2008). It "tests for cross-sectional temporal dependence," with the understanding that institutional investors who follow each other into (out of) the same stocks will statistically be buyers (sellers) of that security over that time period (Sias 2004).

The LSV herding measure has been criticized on a number of issues for which it fails to account. Bikhchandani and Sharma (2000) highlight three main drawbacks: first, it does not distinguish intentional herding, from "spurious herding," which is defined as groups facing similar information sets making similar decisions; second, the LSV measure does not consider trading intensity because it only factors in the number of buyers and sellers regardless of the volume of assets bought or sold; and third, it does not account for identifying inter-temporal trading patterns at the fund level—it can test herding persistence on a stock over time, but not for a particular fund. Additionally, Frey, Herbst, and Walter (2009) propose a new measure of herding in response to the LSV measure only being partially accurate due to often ambiguous results.

The first major departure from the LSV measure is conducted by Sias (2004). Sias (2004) adapted the LSV approach by measuring the cross-sectional temporal dependence directly, i.e., the extent that traders follow each other over adjacent quarters. He estimates a strong and positive correlation between the fraction of institutions buying the same stock over adjacent quarters. This reveals institutional herding and institutions following their own lag trades. Brown, Wei, and Wermers (2013) constructed an adjusted herding measure based on the LSV and Wermers (1999) herding measures. They study mutual funds in response to analyst recommendations and find that mutual funds herd as a reaction to analyst recommendations, more strongly to downgrades than upgrades.

2.2 Impact on Prices

Evidence on herding behavior's impact on prices is diverse. Grinblatt, Titman, and Wermers (1995), Wermers (1999), and Nofsinger and Sias (1999) find a strong positive correlation between changes in institutional ownership and returns over the same period. "Current literature generally concludes that fund managers do engage in conformist trading," but there is less consensus on the price impacts of institutional conformism (Dasgupta 2011). Wermers (1999) and Sias (2004) find that institutional herding drives prices towards fundamental value, whereas Dasgupta, Prat, and Verardo (2011; 1st) find that prices reverse following episodes of institutional herding. Dasgupta, Prat, and Verardo (2011; 2nd) find that assets persistently bought by fund managers trade at prices that are too high, thus experiencing negative long-term returns.

Puckett and Yan (2008) incorporate the LSV (1992) herding measure and the Sias (2004) measure. While long-term herding studies (see Nofsinger and Sias (1999); Wermers (1999); Sias (2004)) generally find that institutional herding is information-based, Puckett and Yan (2008) find this is exhibited in buy herds, "whereas institutional sell herds tend to be driven by liquidity needs or by other behavioral reasons." More specifically, they find strong evidence of return reversals following short-term sell herds and weak evidence of return continuations following short-term buy herds. The most recent research is inconsistent with prior hedge fund crowding findings. Reca, Sias, and Turtle (2014) find that hedge fund equity portfolios are remarkably independent. And, that demand shocks, when hedge funds buy and sell the same stocks, are positively related to subsequent raw and risk-adjusted returns.

2.3 Correlated Strategies

Most herding models suggest that investors follow some common signal. Nofsinger and Sias (1999) identify that institutions may herd as a result of feedback trading, which is the correlation between herding and lag returns. Funds following the same signals, is also suggested by Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994). Among the other reasons institutional investors may choose to herd, Wermers (1999) and Sias (2004) identify a number of explanations; the most compelling of which are herding due to informational cascades and characteristic herding. Informational cascades result from institutional investors ignoring their own information and trading off of information inferred from each other's trades (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992; Wermers 1999). Characteristic herding exists from institutional investors being attracted to securities with specific characteristics (Falkenstein, 1996; Del Guercio, 1996; Gompers and Metrick, 2001; Bennett, Sias, and Starks, 2003).[1] Griffin and Xu (2009) compare hedge funds with mutual funds and find that hedge funds exhibit preferences for medium-sized value stocks and are particularly found in stocks with fewer analysts, higher volatility, less liquidity. This paper recognizes that there are a number of reasons that may compel investors to herd; however, these are less relevant when looking at pairs of institutional investors because this paper is not concerned with the theoretical conclusions of herding, rather it is focused on the tangible presence of herding and its practical implications.

[1] Momentum trading serves as an example of characteristic herding, that is, institutional investors are attracted to (repelled by) securities with high (low) past returns.

3. Data:

This study is based on the original 13F filings by all institutions required to file under section 13(f) of the Securities and Exchange Act of 1934. Currently, institutional investment managers who exercise investment discretion over accounts holding at least $100,000,000 of section 13(f) securities are required to disclose their quarterly holdings within 45 days of the quarter end date. As of 2015 Q2, there are 17,395 such securities requiring disclosure; these include exchange traded and NASDAQ-quoted stocks, equity options, convertible bonds, and shares of closed-end investment companies. Short positions and private securities do not require disclosure. Of such securities, any positions exceeding 10,000 market shares or with market values exceeding $200,000 require disclosure.

I retrieve these filings directly from the SEC's EDGAR database. In Figure 1 of the Appendix, I provide a sample 13F filing from Third Point LLC, a hedge fund located in New York. The figure provides the sample format that all funds are required to use for their filings. My current sample ranges from the first quarter (Q1) of 2015 through the second quarter (Q2) of 2015. First, I remove any filings where the 'period of report' was not 2015 Q1 or Q2. I then remove any equity positions where the CUSIP, number of shares, or value of shares reported are equal to zero, or listed as *NA*. All options and principal positions are removed to only reflect long equity positions. I also keep only the funds that filed both quarters in the sample period. I filter out all funds with less than $100 million in assets under management and holding less than seven stock positions. However, any funds with less than seven stock positions, but with more than $500 million under management are kept in the sample. Additionally, roughly eighty funds filed improperly each quarter, so their reported values are reduced by a factor of one thousand.[2]

Table 1 reports that, in my sample period, 3,382 institutions had filings in both 2015 Q1 and Q2, 3,036 (90%) of which are located in the United States. The average institutional investment fund during this period holds 290 distinct equities and has $6.4 billion AUM. Foreign funds are on average larger in both AUM and number of stocks held than are funds located in the United States.

Table 1
Descriptive Statistics

2015 Q1 & Q2 Average	**Mean**	**Median**	**Max**	**Sum (*Distinct*)**
	All Funds (n = 3382)			
AUM ($000s)	6,381,506	533,536	1,546,977,977	22,165,403,373
No. of Stocks	290	105	6,634	*19,405*
	Domestic Funds (n = 3036)			
AUM ($000s)	6,150,259	482,675	1,546,977,977	18,672,185,896
No. of Stocks	279	106	6,404	*16,016*
	Foreign Funds (n = 346)			
AUM ($000s)	8,410,593	1,526,872	183,682,992	2,910,065,186
No. of Stocks	390	103	6,634	*7,468*
	Fifth Quintile Funds (AUM and Stocks) (n = 346)			
AUM ($000s)	48,378,711	13,014,616	1,546,977,977	16,714,951,284
No. of Stocks	1,444	943	6,634	*13,549*
	First Quintile Funds (AUM and Stocks) (n = 173)			
AUM ($000s)	145,160	144,795	194,873	25,037,281
No. of Stocks	21	20	35	*1,997*

[2] While institutional investment funds are responsible for disclosing the nominal market value (in $000s) of each equity position, some do not do so properly. Roughly three percent filed at full value, which would inflate their AUM by a factor of one thousand and throw off the data.

Table 2 presents a breakdown of assets under management for all funds in the sample: 48% are less than \$500 million; 16.8% are between \$500 million and \$1 billion; 26.7% are between \$1 billion and \$10 billion; and 8.5% are greater than \$10 billion, with 1% greater than \$100 billion. The largest institution exercises investment discretion of over \$1.5 trillion of long equity positions.[3] Average aggregate total assets under management for the period are \$21.6 trillion and my sample consisted of 1,961,905 distinct equity positions.

Table 2
Assets Under Management (AUM) Breakdown

2015 Quarter	Total	Number of Funds by AUM Size					
		< \$500M	\$500M - \$1B	\$1B - \$10B	\$10B - \$50B	\$50B - \$100B	> \$100B
1	3,382	1,628	567	900	214	38	35
2	3,382	1,617	570	905	217	37	36
	% Total	48.0%	16.8%	26.7%	6.4%	1.1%	1.0%

There are three significant limitations in the data. First, 13F data do not provide insight into intraquarter institutional trades. Second, the data only reveal long equity positions. A notable portion of institutional investment funds are hedge funds whose strategies often involve less-regulated and more unique trading techniques, involving the use of derivatives and short positions, which are not observable in my data. Tangentially, the data do not provide enough information for classifying funds individually (e.g. hedge fund, mutual fund, bank, etc.). Finally, there exists an exception where investment managers can request confidential treatment of some or all of their positions to delay disclosure. However, these filings are not included, as they are not relevant to this study for two reasons. First, my focus is on information injected into the market from initial public filings; and second, because Agarwal, Jiang, Tang, and Yang (2010) show that in their study

[3] This is the Vanguard Group, based out of Pennsylvania. Over the course of the sample period, the eight largest funds ranked the same each quarter, and the top 25 all remained in the top 25 in some order. Of the top 25 largest funds, six are located in California and five are located in both New York and Massachusetts.

of all 13F filings from 1999-2007, only 7.2% of institutions have resorted to confidential filing at least once.

4. Methodology:

I measure the extent to which institutional investors herd by examining the overlap in their portfolios. As I am testing 3,382 individual funds, I am going to have nearly 11.5 million (11,434,542) institutional fund pairs for each quarter to use as observations of portfolio overlap.[4] My methodology draws from Reca, Sias, and Turtle's (2014) measure to test for hedge fund portfolio overlap and independence, but I expand this to all institutional investors. Additionally, I study the effect time has on a fund's likelihood to follow.

Reca, Sias, and Turtle (2014) measure portfolio overlap in four different ways, the third of which is relevant for this study—the cosine similarity measure. Additionally, I am going to perform intertemporal regressions to hopefully reveal which groups of institutional investment funds are the leaders and which groups are the followers (i.e. the herders). The dependent variable is going to be the similarity among portfolios, and the independent variables are going to be the characteristics of the institutional investment funds that most explain the similarity. These characteristics will focus on fund size and location mostly. Unlike the popular Lakonishok, Shleifer, and Vishny (1992) herding measure, which is based off of the assumption that no herding exists, these tests are not going to have null hypotheses of no similarity. This is a safe assumption, because a large literature base has confirmed that different types of institutional investors exhibit

[4] There are, in fact, 11,437,924 pairs, however I eliminate 3,382 pairs accounting for the fact that each fund will be paired with itself once. The result is 11,434,542 pairs each quarter.

preferences for securities with specific characteristics (see Grinblatt, Titman, and Wermers (1995); Falkenstein (1996); Bennett, Sias, and Starks (2003); and Griffin and Xu (2009)).

4.1 Cosine Similarity

The cosine similarity measure calculates the product of the overlapping portfolio weights. The equation is as follows:

$$s(h_t, j_t) = \sum_{k=1}^{K} w_{h,k,t} w_{j,k,t} \Bigg/ \left(\sqrt{\sum_{k=1}^{K} w_{h,k,t}^2} \sqrt{\sum_{k=1}^{K} w_{j,k,t}^2} \right).$$

Specifically, I am looking at the cosine similarity between institutional investor *h*'s portfolio weights and institutional investor *j*'s portfolio weights. Here *K* is the total number of securities in the market in quarter *t*, $w_{h,k,t}$ is institutional investor *h*'s quarter *t* portfolio weight in security *k*, and $w_{j,k,t}$ is institutional investor *j*'s quarter *t* portfolio weight in security *k*.

Cosine similarity ranges between zero and one, so two exactly equal portfolios will result in a value of one. Conversely, two portfolios that hold no equities in common will have a cosine similarity of zero.

5. Empirical Results:

This section presents the empirical results of calculating the cosine similarity between pairs of funds. It begins with a discussion of the contemporaneous similarities between funds and includes supplementary summary tables. This is followed by several regression analyses that provide insight into the drivers of contemporaneous cosine similarity. Next I discuss the similarities over time and analyze the intertemporal effect on the drivers of cosine similarity. Then I focus on New York and California-specific funds to see how portfolio overlap is either amplified or reduced in those saturated regions. I conclude this section with a regression for each of the regions which continue using intertemporal cosine similarity as the dependent variable, but controls for the contemporaneous similarity.

5.1 Contemporaneous Similarity

Table 3 shows the average cosine similarity of institutional fund pairs in 2015 Q2.[5] Cosine similarity is 0.074 for all funds. Foreign funds are a bit more similar to each other than are domestic funds (with an average cosine similarity of 0.098 vs. 0.073).

Table 3
Contemporaneous Cosine Similarity Descriptive Statistics

2015 Q2 Cosine Similarity	Mean	Median	Std. dev.	No. Obs.
All Funds	0.074	0.022	0.115	11,434,542
		Location Based		
Domestic	0.073	0.021	0.114	9,214,260
Foreign	0.098	0.037	0.145	119,370
Domestic -> Foreign	0.076	0.024	0.118	1,050,456
Same Code	0.058	0.012	0.102	844,172
Different Code	0.075	0.023	0.116	10,590,370
		AUM Quintile		
5th Quintile Only	0.145	0.078	0.177	456,300
1st Quintile Only	0.059	0.014	0.095	457,652
5 -> All	0.090	0.034	0.127	1,829,256
1 -> All	0.066	0.018	0.104	1,831,285
		No. of Stocks Quintile		
5th Quintile Only	0.225	0.170	0.199	456,300
1st Quintile Only	0.010	0.000	0.043	468,540
5 -> All	0.104	0.051	0.095	1,829,256
1 -> All	0.024	0.001	0.055	1,847,445

[5] Cosine similarity in 2015 Q1 is nearly identical to 2015 Q2, so the following results are from 2015 Q2, unless otherwise noted.

Contrary to intuition, pairs of funds that are located in the same geographic code are more independent than are pairs located in different geographic codes (cosine similarity is 0.058 and 0.075, respectively).[6] Pairs of large funds are much more similar to each other than are pairs of small funds (0.059 and 0.145, respectively).[7] However, there is a much stronger relationship between funds that have a comparable number of equity positions. Comparable fund pairs in the highest quintile for number of equity positions held are over 20 times more similar than are fund pairs that are both in the lowest quintile (0.225 and 0.010, respectively). It makes sense that the institutions which typically exhibit more similarity have portfolios with a high number of equity positions and large assets under management. This is due to the fact that these massive and highly-diversified funds are typically not hedge funds which seek absolute returns, but are more likely to take after mutual funds which seek benchmarked returns. The very nature of a benchmark index innately will be more conducive to similar portfolios. However, the correlation between a highly diversified equity portfolio and a higher cosine similarity is much greater than the impact of a high level of AUM.[8]

5.2 Drivers of Contemporaneous Similarity

In this section, I examine the drivers of contemporaneous cosine similarity through a regression analysis. Table 4 reports my results controlling for several fund characteristics, including portfolio size, diversification level, and geographic differences. Each of the independent variables are dummy variables whose value is equal to one if both funds in a pair share the same quintile, code, or country, and zero otherwise. In all cases, I find these results are statistically significant at the

[6] Geographic codes are at the state (province) level for the United States (Canada) and are at the country level for all other foreign funds. See Table A and Table B in the Appendix for a breakdown of funds by state and by country.
[7] All funds were categorized into five quintiles by AUM and the number of equity positions (stocks) held (i.e. a fund in the largest quintile for both AUM and stocks held will have a 5 in both quintile variables).
[8] Refer to Figure 2 and Figure 3 in the Appendix for a visual representation of the two correlations.

1% level. The results in Table 4 in all four columns are consistent with the statistics reported in Table 3 in regard to the negative relationship between geographically similar funds and cosine similarity. I also find that when a pair of funds are in the same quintile for the number of equity positions held, there is a positive effect on cosine similarity and that the same holds true for AUM quintile, though not as strongly. The two most significant drivers appear to be the *Same Stocks Quintile* and *Same Code* explanatory variables as having a positive and a negative effect, respectively, on cosine similarity.

Table 4
Drivers of Contemporaneous Similarity (2015 Q2)

	Dependent Variable: Cosine Similarity			
	(1)	(2)	(3)	(4)
Same AUM Quintile	0.005***	0.005***	0.005***	0.005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Stocks Quintile	0.025***	0.025***	0.025***	0.025***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Code		-0.018***		-0.018***
		(0.0001)		(0.0001)
Same Country			-0.003***	-0.002***
			(0.0001)	(0.0001)
Constant	0.068***	0.069***	0.071***	0.070***
	(0.00004)	(0.00004)	(0.0001)	(0.0001)
Observations	11,434,542	11,434,542	11,434,542	11,434,542
R^2	0.008	0.01	0.008	0.01
Note:				*p<0.1;**p<0.05;***p<0.01

The first through fourth columns show that a pair of funds in the same number of equity positions quintile are associated with having a 0.025 higher cosine similarity than a pair of funds that are in different quintiles. Conversely, those columns show that a pair of funds located in the same geographic code are associated with having a 0.018 lower cosine similarity than funds in different geographic codes.

In attempt to break down the full effects of AUM and the number of equity positions, Table 5 reports the correlation of not only the same AUM or number of equity positions on cosine similarity, but also each individual quintile level. Again, all results are statistically significant at the 1% level. The results in the first two columns of Table 5 are nearly identical to the result in the first column of Table 4.

Table 5
Contemporaneous - Comparable AUM and Stock Quintiles (2015 Q2)

	Dependent Variable: Cosine Similarity			
	(1)	(2)	(3) By AUM Quintile	(4) By Stock Quintile
Same AUM Quintile	0.006***			
	(0.0001)			
Same Stocks Quintile		0.025***		
		(0.0001)		
Fifth Quintile			0.072***	0.156***
(AUM / # of Stocks)			(0.0002)	(0.0002)
Fourth Quintile			-0.010***	0.052***
(AUM / # of Stocks)			(0.0002)	(0.0002)
Third Quintile			-0.002***	0.012***
(AUM / # of Stocks)			(0.0002)	(0.0002)
Second Quintile			-0.015***	-0.034***
(AUM / # of Stocks)			(0.0002)	(0.0002)
First Quintile			-0.014***	-0.059***
(AUM / # of Stocks)			(0.0002)	(0.0002)
Constant	0.073***	0.069***	0.073***	0.069***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Observations	11,434,542	11,434,542	11,434,542	11,434,542
R^2	0.0005	0.008	0.017	0.094
Note:				*p<0.1;**p<0.05;***p<0.01

The third column of Table 5 shows that only pairs of funds having the same AUM level in the fifth quintile are more similar to each other than pairs of funds where each fund belongs to a different quintile. The fourth column shows a more optimistic set of drivers behind the different number of stock quintiles. Pairs of funds that both have a number of equity positions in the third quintile or higher are increasingly more similar than are pairs where both funds are in the lowest two quintiles. The R-squared value in the fourth column shows that the explanatory dummy variables indicating fund pairs that have a similar number of equity positions explains the variation in cosine similarity by 9.4%, whereas the analogous case for fund size only explains a fraction of the variation in similarity at 1.7%.

5.3 Similarity Over Time

This section discusses the portfolio overlap over time between 2015 Q1 and 2015 Q2. The goal is to identify which funds, either specifically or more generally (i.e. groups of funds), seem to lead and which funds seem to follow. By comparing the portfolios of funds in 2015 Q1 with those of funds in 2015 Q2, I intend to better identify the presence of herding. If, for instance, we see much higher portfolio overlap (i.e. a high cosine similarity) in fund i's quarter t portfolio with fund j's quarter t-1 portfolio than in both fund i's quarter t-1 portfolio and fund j's quarter t-1 portfolio, and fund i's quarter t portfolio and fund j's quarter t-1 portfolio, then we can conclude that, to an extent, fund i is following fund j. While association and causation can play potential roles in this conclusion, the goal is to compare funds on a much larger scale and in the aggregate.

Table 6 reports the average intertemporal cosine similarity of institutional fund pairs in between Q1 and Q2 of 2015. The intertemporal cosine similarity is 0.073 for all funds and 0.072 and 0.098 for domestic only and foreign only fund pairs, respectively. These results are nearly identical to those found in the contemporaneous tests for 2015 Q2 and for 2015 Q1 (Table 3). The intertemporal average cosine similarity of domestic funds in 2015 Q1 compared with foreign funds in 2015 Q2 (0.074) is lower than the converse, 0.077 (i.e. the cosine similarity of foreign funds in

2015 Q1 with domestic funds in 2015 Q2), which means that domestic funds are following, though slightly, foreign funds.

Table 6
Intertemporal Cosine Similarity Descriptive Statistics

2015 Q1 — Q2 Cosine Similarity	Mean	Median	Std. dev.	No. Obs.
All Funds	0.073	0.021	0.114	11,434,542
		Location Based		
Domestic	0.072	0.020	0.113	9,214,260
Foreign	0.098	0.038	0.146	119,370
Domestic -> Foreign	0.074	0.023	0.117	1,050,456
Foreign -> Domestic	0.077	0.024	0.119	1,050,456
Same Code	0.056	0.011	0.101	845,050
Different Code	0.074	0.022	0.115	10,589,492
		AUM Quintile		
5th Quintile Only	0.145	0.077	0.177	456,323
1st Quintile Only	0.058	0.013	0.093	457,701
5 -> All	0.090	0.034	0.128	1,829,233
All -> 5	0.088	0.033	0.125	1,829,233
1 -> All	0.064	0.016	0.102	1,831,236
All ->1	0.066	0.017	0.104	1,831,236
		No. of Stocks Quintile		
5th Quintile Only	0.225	0.171	0.199	454,302
1st Quintile Only	0.010	0.000	0.042	469,256
5 -> All	0.104	0.050	0.129	1,821,111
All -> 5	0.102	0.050	0.127	1,831,254
1 -> All	0.023	0.001	0.054	1,850,110
All -> 1	0.024	0.001	0.055	1,846,729

Also in line with the contemporaneous findings, funds that are located in the same geographic code are more independent, intertemporally, than are pairs located in different geographic codes (cosine similarity is 0.056 and 0.074, respectively). Interestingly, I find that most reported results in the intertemporal test show slightly lower values of cosine similarity than their analogous contemporaneous result. The average cosine similarity of comparably-sized funds is effected much more by pairs of large funds than it is by pairs of small funds (0.058 and 0.145, respectively). A much stronger relationship exists, intertemporally, between a fund's number of equity positions (i.e. a fund's level of diversification) and its average cosine similarity. Identical to the contemporaneous test in 2015 Q2, comparable fund pairs that hold the most positions are more than 20 times less independent, intertemporally, than are fund pairs in the lowest quintile (0.225 and 0.010, respectively). In short, the regressions that follow will provide evidence that the positively-correlated impact of portfolios with a lot of equity positions on cosine similarity is much greater than the positively-correlated impact of a high level of AUM.

5.4 Drivers of Similarity Over Time

In this section, I examine the drivers of intertemporal cosine similarity through a regression analysis. Table 7 reports my results controlling for several fund characteristics, including portfolio size, diversification level, and geographic differences. Each of the independent variables are dummy variables whose value is equal to one if both funds in a pair have the same quintile, code, or country, and zero otherwise. In all cases, I find these results are statistically significant at the 1% level. The results in all four columns of Table 7 are closely related to the regressions presented in Table 4 and are consistent with the statistics reported in Table 6 in regard to the negative relationship between geographically similar funds and cosine similarity. In line with the contemporaneous results, the two most significant drivers appear to be the number of equity positions and geographic code as having a positive and a negative effect, respectively, on cosine similarity.

Table 7
Drivers of Intertemporal Similarity (2015 Q1 — Q2)

	Dependent Variable: Cosine Similarity			
	(1)	(2)	(3)	(4)
Same AUM Quintile	0.005***	0.005***	0.005***	0.005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Stocks Quintile	0.025***	0.025***	0.025***	0.025***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Code		-0.019***		-0.018***
		(0.0001)		(0.0001)
Same Country			-0.004***	-0.002***
			(0.0001)	(0.0001)
Constant	0.067***	0.068***	0.070***	0.070***
	(0.00004)	(0.00004)	(0.0001)	(0.0001)
Observations	11,434,542	11,434,542	11,434,542	11,434,542
R^2	0.008	0.01	0.008	0.01
Note:			*p<0.1;**p<0.05;***p<0.01	

However, these results basically mirror whether or not a pair of funds has similar 2015 Q2 portfolios. Additionally, the low R-Squared values show that the independent variables explain only a tiny fraction of the variation in similarity.

Table 8 reports the intertemporal correlation of not only the same AUM or number of equity positions on cosine similarity, but also each individual quintile level.

Table 8
Intertemporal - Comparable AUM and Stock Quintiles (2015 Q1 — Q2)

	Dependent Variable: Cosine Similarity			
	(1)	(2)	(3) By AUM Quintile	(4) By Stock Quintile
Same AUM Quintile	0.006***			
	(0.0001)			
Same Stocks Quintile		0.025***		
		(0.0001)		
Fifth Quintile (AUM / # of Stocks)			0.073***	0.157***
			(0.0002)	(0.0002)
Fourth Quintile (AUM / # of Stocks)			-0.011***	0.050***
			(0.0002)	(0.0002)
Third Quintile (AUM / # of Stocks)			-0.004***	0.013***
			(0.0002)	(0.0002)
Second Quintile (AUM / # of Stocks)			-0.013***	-0.034***
			(0.0002)	(0.0002)
First Quintile (AUM / # of Stocks)			-0.014***	-0.058***
			(0.0002)	(0.0002)
Constant	0.072***	0.068***	0.072***	0.068***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Observations	11,434,542	11,434,542	11,434,542	11,434,542
R^2	0.0005	0.008	0.018	0.096
Note:				*p<0.1;**p<0.05;***p<0.01

Again, all results are statistically significant at the 1% level. Similar to the closeness between Table 4 and Table 7, Table 8 reports nearly identical coefficients to the values reported in Table 5. In line with the results of other regressions and averages, a fund's AUM level has the most intertemporal predictive power when both funds have the same level and that level is the fifth quintile. Additionally, while the same holds true for fund pairs that share the highest level of equity positions in comparison to lower shared levels, the positive effect is much higher for the number of stock positions than AUM and is still the biggest driver of cosine similarity.

5.5 Herding in New York and California

Two particularly relevant subsets of the data are New York funds, which contain the highest number of institutional investment funds relative to other states or countries, and California-based funds, the second densest state-level location. Of the 3,382 funds, 715 were located in New York, followed by California with half that at 357 funds. Intuitively, these overcrowded investment hubs should reflect a higher level of herding, however the results reveal that, in fact, the opposite is true—cosine similarity, on average is lower in these states than it is for all funds in the sample.

Table 9
New York and California Funds – Descriptive Statistics

2015 Q1 & Q2 Avg	Mean	Median	Max	Sum (*Distinct*)
		New York Funds		
AUM ($000s)	5,954,693	646,597	407,147,922	4,263,571,233
No. of Stocks	259	59	6,404	*9,958*
Cosine Similarity	0.042	0.006		
		California Funds		
AUM ($000s)	8,904,472	465,389	631,859,685	3,174,434,134
No. of Stocks	244	91	5,721	*8,808*
Cosine Similarity	0.065	0.015		

Table 9 reports some of the descriptive statistics of New York and California-based funds over my sample period. Both fund groups have a lower cosine similarity than the overall average, and New York is dragging heavily upon overall cosine similarities as a result.

Table 10 reports the average intertemporal cosine similarity for New York and California-based funds to explore whether or not these investment hubs lead outside funds. As presented in the contemporaneous results for cosine similarity, the data is consistently skewed right (i.e. the distribution is not symmetric around the mean, but the mean is greater than the median). In particular, CA funds typically are shown to have a higher standard deviation in their intertemporal cosine similarities with other funds than that of analogous NY funds.

Table 10
NY & CA — Intertemporal Similarity Descriptive Statistics

2015 Q1 — Q2 Cosine Similarity	Mean	Median	Std. dev.	No. Obs.
All Funds	0.074	0.022	0.115	11,434,542
		Location Based		
NY Only	0.041	0.006	0.079	511,940
CA Only	0.065	0.015	0.107	126,736
NY -> CA	0.048	0.007	0.091	255,969
CA -> NY	0.047	0.007	0.09	254,540
NY -> All	0.054	0.010	0.098	1,912,237
All -> NY	0.054	0.011	0.097	1,905,475
CA -> All	0.068	0.018	0.110	1,076,900
All -> CA	0.069	0.018	0.111	1,080,281
		NY (AUM & No. of Stocks Quintile)		
5th Quintile Only	0.246	0.078	0.203	4,225
1st Quintile Only	0.010	0.000	0.037	3,668
5 -> All	0.279	0.232	0.216	18,348
All -> 5	0.273	0.225	0.216	18,330
1 -> All	0.008	0.000	0.036	6,540
All -> 1	0.008	0.000	0.040	7,068
		CA (AUM & No. of Stocks Quintile)		
5th Quintile Only	0.389	0.389	0.251	506
1st Quintile Only	0.015	0.000	0.055	733
5 -> All	0.345	0.317	0.239	7,360
All -> 5	0.335	0.299	0.24	7,475
1 -> All	0.011	0.000	0.045	4,032
All -> 1	0.011	0.000	0.043	3,942

The data show that the average cosine similarity between all funds in NY in 2015 Q1 and all funds in CA in 2015 Q2 is nearly equal to the converse—the overlap of CA funds' 2015 Q1 portfolios and of NY funds' 2015 Q2 portfolios. I understand this to be that New York funds follow California funds just as much as CA funds follow NY funds, though the follower effect is very small in these cases. Similarly, this result exists between the different number of equity positions and fund-size slices of the funds when compared intertemporally with all other funds in the sample.

Table 11 reports the intertemporal relationship between NY and CA funds and each of those groups in comparison to all other funds. To interpret the regressions panel, the independent dummy variables are the same for both the top section, which corresponds to a NY fund in 2015 Q1, and the bottom section, which corresponds to a CA fund in 2015. The first column is a regression of either NY or CA funds on NY funds in 2015 Q2. The second column is the same, but with CA funds in 2015 Q2. Column 3 in Table 11 can be interpreted as either NY or CA funds' portfolio in 2015 Q1 compared to that of all the portfolios in 2015 Q2 of funds exclusive of either NY or CA. The last column is the converse of this, and reflects the regressed results of portfolio overlap of all 2015 Q1 portfolios of funds that are exclusive of either NY or CA with the portfolios of either NY or CA funds.

Table 11
NY & CA — Drivers of Intertemporal Similarity (2015 Q1 — Q2)

		Dependent Variable: Cosine Similarity			
		(1)	(2)	(3)	(4)
		NY	**CA**	**Against All Other**	**All Other Against**
NY	Same AUM	0.007***	0.004***	0.005***	0.006***
		(0.0003)	(0.0005)	(0.0002)	(0.0002)
	Same Stocks	0.003***	0.007***	0.018***	0.018***
		(0.0003)	(0.0004)	(0.0002)	(0.0002)
	Constant	0.038***	0.046***	0.050***	0.049***
		(0.001)	(0.0002)	(0.001)	(0.001)
	Observations	511,940	255,969	1,912,237	1,905,475
	R^2	0.002	0.001	0.006	0.006
CA	Same AUM	0.005***	0.002**	0.004***	0.003***
		(0.0004)	(0.001)	(0.0003)	(0.0003)
	Same Stocks	0.006***	0.012***	0.018***	0.019***
		(0.0004)	(0.001)	(0.0003)	(0.0003)
	Constant	0.045***	0.062***	0.064***	0.064***
		(0.0002)	(0.0004)	(0.001)	(0.001)
	Observations	254,540	126,736	1,076,900	1,080,281
	R^2	0.001	0.002	0.004	0.005
Note:					*p<0.1;**p<0.05;***p<0.01

Intertemporally, similarity between NY-only fund pairs is driven more by similarity in overall portfolio size than similarities in the number of stocks held by the funds. This is incongruous with nearly every other regression, regardless of whether or not the sample size reflected my entire fund sample or a subsample of funds. The coefficient for NY funds in 2015 Q1 having a similar number of equity positions with all non-NY funds in 2015 Q2 is equal to the opposite comparison (i.e. the fourth column) which indicates that New York funds follow (do not follow) all other funds just as much as all other funds follow (do not follow) NY funds. The coefficients for the same number of equity positions independent dummy variable for CA funds regressed on all other funds and vice versa in the third and fourth columns, respectively, would suggest that CA funds are following, though slightly, the equity portfolios of other funds, rather than the alternative; however, this is offset by the equally significant same AUM-quintile explanatory variable so that CA funds follow all other funds to the same extent that other non-CA funds are following CA funds.

I find that intertemporal cosine similarity, which is a more effective measure for identifying herding, is mostly driven by the contemporaneous similarity in 2015 Q1. I run a final set of regressions for intertemporal similarity with the contemporaneous similarity as one of the explanatory variables to control for the fact that the contemporaneous similarity of fund pairs in 2015 Q1 is going to explain the majority of the intertemporal similarity. I present the results in Table 12 to explain what drives intertemporal similarity, controlling for contemporaneous similarity. All coefficients are statistically significant at the 1% level, except for the second coefficient in column two, which is significant at the 10% level. The first explanatory variable is *Q1 Cosine Similarity* which is that fund pair's contemporaneous 2015 *Q1 cosine similarity*. The two explanatory dummy variables below the variable controlling for Q1 similarity are related to NY funds in the first column and CA funds in the second column.

Table 12
Intertemporal Similarity, Controlling for Contemporaneous — NY & CA

	Dependent Variable: Cosine Similarity		
	(1)		(2)
Q1 Cosine Similarity	0.979***		0.980***
	(0.0001)		(0.0001)
NY Q1, non-NY Q2	-0.001***	CA Q1, non-CA Q2	0.00004*
	(0.00002)		(0.00002)
NY Q2, non-NY Q1	-0.001***	CA Q2, non-CA Q1	0.001***
	(0.00002)		(0.00002)
Constant	0.001***		0.001***
	(0.00001)		(0.00001)
Observations	11,434,542		11,434,542
R^2	0.966		0.966
Note:			*p<0.1;**p<0.05;***p<0.01

Controlling for contemporaneous similarity, the negative coefficients for NY funds indicate that non-NY funds do not follow New York funds and NY funds do not follow the rest of the world. The positive coefficients for CA funds suggest that funds exclusive of CA are following CA funds and that the opposite is true. As the bottom dummy variable is much greater than the other dummy variable, the intertemporal similarity is much higher in pairs that involve a CA fund in 2015 Q2, suggesting CA funds follow all other funds more intensely than do CA funds lead all other funds. These findings imply that both the strategies New York funds pursue and their portfolio moves are different from the rest of the world.

6. Conclusion:

I analyze the similarity of institutional investment fund holdings in equity positions contemporaneously and over time. I compiled data on over 3,000 distinct institutional investment funds from their publicly-filed 13F reports in the first two quarters of 2015. While my results reveal that there is a relatively low level of similarity between funds overall, I do find that there are certain characteristics that drive cosine similarity, both contemporaneously and over time. I find statistically significant evidence that, contrary to intuition, pairs of institutional investment funds exhibit less portfolio overlap when they are positioned in the same geographic code than when they are from different geographic codes. Although, this is driven largely by the fact that funds located in New York are very dissimilar to each other. Even after excluding all NY funds from the data, there was little change in the two strongest (no. of equity positions and code) drivers of similarity; however, a sign change for the country dummy variable indicates that NY funds were causing it originally to be slightly negative.[9] I also find that fund pairs in the same quintile for their AUM level or their number of equity positions show a higher level portfolio overlap. This effect is significantly more pronounced and persistent for the number of equity positions of funds than it is for the size of the funds. Similarity in fund size drives portfolio similarity only for pairs of funds that are in the highest quintile. However, there is empirical evidence that the positive correlation for funds which share the same quintile for their number of equity positions persists in the top three quintiles both contemporaneously and intertemporally. The New York and California subsamples of funds actually display lower levels of portfolio overlap on average than do all funds in general. As New York is substantially less similar than the sample as a whole and the California

[9] Refer to Table C in the Appendix where I present the results for both contemporaneous and intertemporal similarity for all funds and all funds excluding NY funds. Removing NY funds from the sample resulted in the same country explanatory variable changing from -0.002 (for all funds) to 0.005.

subsample, and because it accounts for over 20 percent of the entire reporting sample of funds, it skews the data to the right (i.e. means are consistently greater than medians). Overall, I find that intertemporal cosine similarity is driven almost exclusively by contemporaneous similarity.

This study is limited by the data in three ways: first, my sample is only over the course of two quarters, which is a much shorter time frame than much of the extant related literature; second, the 13F reports do not provide insight into intraquarter institutional trades, such that a reported position could have been taken months ago or only a few days prior to quarter end; and third, submission standards for 13F filings are low and as a result, there are reporting inconsistencies in the data. Additionally, the data are skewed to the right, which indicates that my linear regression models may be able to be improved upon.

One of the most surprising findings was the lack of patterns in similarity over time. I find no evidence that New York funds are leading the rest of the institutional investment world in investment portfolio holdings. Nor do I find any strong evidence that foreign funds follow US funds, or that small funds follow big funds. I believe that my study would have been strengthened if I were able to better categorize individual funds as hedge funds, mutual funds, banks, etc. Additionally, portfolios of famous investors, many of whom filed reports that were included in my data, and their unique investment strategies are often scrutinized by the press, which seems to contradict the results of funds being mostly independent.

Similar to Reca, Sias and Turtle (2014), whose methodology I adapt, I find that equity portfolios are surprisingly more independent that I originally expected. However, some studies do find a much stronger presence of herding. Sias (2004) reports a strong positive correlation between institutions buying stocks over adjacent quarters. I attribute some of my results to the fact that I am limited by my data which are not nearly as large of a sample size as are in some of the relevant literature. Academically, this study should stimulate more research into the characteristics that drive similarity among institutional funds. From a practical perspective, identifying which funds tend to lead rather than follow could be a proxy for the independence of its investment research.

7. Appendix:

Figure 1

13F Filing Example -- Third Point LLC (2015 Q2)

COLUMN 1	COLUMN 2	COLUMN 3	COLUMN 4	COLUMN 5			COLUMN 6	COLUMN 7	COLUMN 8		
			VALUE	SHRS OR	SH/	PUT/	INVESTMENT	OTHER			
NAME OF ISSUER	TITLE OF CLASS	CUSIP	(x$1000)	PRN AMT	PRN	CALL	DISCRETION	MANAGER	SOLE	SHARED	NONE
ALLERGAN PLC	SHS	G0177J108	1,001,418	3,300,000	SH		SOLE		3,300,000	0	0
ALLY FINL INC	COM	02005N100	224,300	10,000,000	SH		SOLE		10,000,000	0	0
AMERICAN INTL GROUP INC	COM NEW	26874784	216,370	3,500,000	SH		SOLE		3,500,000	0	0
AMGEN INC	COM	31162100	1,381,680	9,000,000	SH		SOLE		9,000,000	0	0
ANHEUSER BUSCH INBEV SA/NV	SPONSORED ADR	03524A108	211,172	1,750,000	SH		SOLE		1,750,000	0	0
ANHEUSER BUSCH INBEV SA/NV	SPONSORED ADR	03524A108	150,838	1,250,000	SH	Call	SOLE		1,250,000	0	0
APIGEE CORP	COM	03765N108	31,444	3,166,551	SH		SOLE		3,166,551	0	0
BAXTER INTL INC	COM	71813109	276,224	3,950,000	SH		SOLE		3,950,000	0	0
BAXTER INTL INC	EX DISTRIB WI	71813141	34,223	900,600	SH		SOLE		900,600	0	0
CHARTER COMMUNICATIONS INC D	CL A NEW	16117M305	17,125	100,000	SH		SOLE		100,000	0	0
CITIGROUP INC	*W EXP 01/04/201	172967226	14,800	20,000,000	SH		SOLE		20,000,000	0	0
COBALT INTL ENERGY INC	NOTE 2.625%12/0	19075FAA4	59,004	80,000,000	PRN		SOLE		80,000,000	0	0
CONSTELLATION BRANDS INC	CL A	21036P108	220,438	1,900,000	SH		SOLE		1,900,000	0	0
DELTA AIR LINES INC DEL	COM NEW	247361702	112,970	2,750,000	SH		SOLE		2,750,000	0	0
DEVON ENERGY CORP NEW	COM	25179M103	223,088	3,750,000	SH		SOLE		3,750,000	0	0
DOW CHEM CO	COM	260543103	1,176,910	23,000,000	SH		SOLE		23,000,000	0	0
EBAY INC	COM	278642103	481,920	8,000,000	SH		SOLE		8,000,000	0	0

Note: This is only a sample of the full report. This filing can be found at: http://www.sec.gov/Archives/edgar/data/1040273/000108514615001835/xslForm13F_X01/form13fInfoTable.xml

Figure 2
All Funds by AUM Level

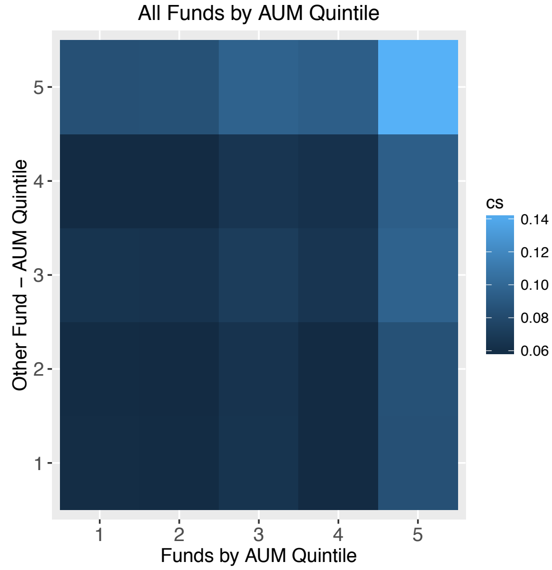

Figure 3
All Funds by Number of Equity Positions

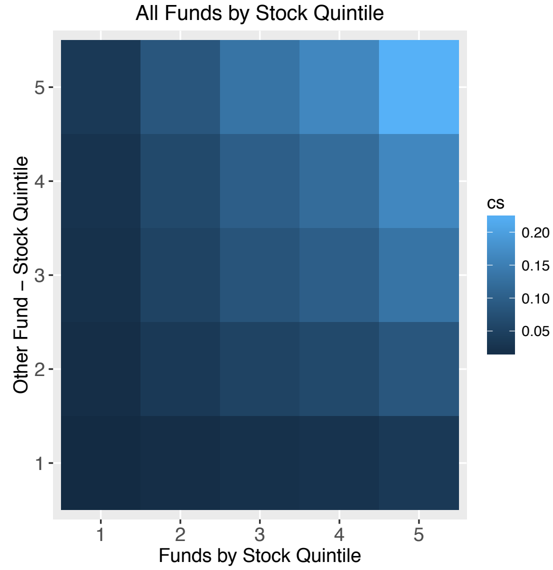

Table A
Funds by State (Code)

Country	No. of Funds	Country	No. of Funds
ALASKA	3	MONTANA	5
ALABAMA	15	NORTH CAROLINA	44
ARKANSAS	13	NORTH DAKOTA	3
ARIZONA	15	NEBRASKA	23
CALIFORNIA	357	NEW HAMPSHIRE	15
COLORADO	46	NEW JERSEY	86
CONNECTICUT	136	NEW MEXICO	4
DC	6	NEVADA	5
DELAWARE	19	NEW YORK	715
FLORIDA	73	OHIO	79
GEORGIA	61	OKLAHOMA	10
HAWAII	5	OREGON	24
IOWA	12	PENNSYLVANIA	149
IDAHO	4	RHODE ISLAND	16
ILLINOIS	174	SOUTH CAROLINA	7
INDIANA	23	SOUTH DAKOTA	2
KANSAS	23	TENNESSEE	39
KENTUCKY	23	TEXAS	147
LOUISIANA	9	UTAH	9
MASSACHUSETTS	216	VIRGINIA	68
MARYLAND	62	VERMONT	12
MAINE	11	WASHINGTON	47
MICHIGAN	57	WISCONSIN	49
MINNESOTA	53	WEST VIRGINIA	7
MISSOURI	50	WYOMING	2
MISSISSIPPI	3		

Table B
Funds by Country

Country	No. of Funds	Country	No. of Funds
AUSTRALIA	10	ISRAEL	10
BAHAMAS	5	ITALY	1
BELGIUM	2	JAPAN	30
BERMUDA	2	JERSEY	3
BRAZIL	2	SOUTH KOREA	3
CANADA	89	LUXEMBOURG	3
CAYMAN ISLANDS	3	MONACO	1
CHINA	1	NETHERLANDS	11
DENMARK	2	NEW ZEALAND	1
FRANCE	9	NORWAY	3
GEORGIA	1	SINGAPORE	5
GERMANY	8	SOUTH AFRICA	2
GUERNSEY	2	SWEDEN	10
HONG KONG	10	SWITZERLAND	20
IRELAND	2	UNITED KINGDOM	93
ISLE OF MAN	2	UNITED STATES	3036

Table C
Contemporaneous and Intertemporal Similarity Excluding NY Funds

	Dependent Variable: Cosine Similarity			
	Contemporaneous		**Intertemporal**	
	(1)	(2)	(3)	(4)
	w/ NY	w/o NY	w/ NY	w/o NY
Same AUM Quintile	0.005***	0.004***	0.005***	0.004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Stocks Quintile	0.025***	0.030***	0.025***	0.030***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Code	-0.018***	-0.007***	-0.018***	-0.007***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Same Country	-0.002***	0.005***	-0.002***	0.005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	0.070***	0.076***	0.070***	0.075***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	11,434,542	7,110,222	11,434,542	7,104,890
R^2	0.01	0.01	0.01	0.01
Note:			*p<0.1; **p<0.05; ***p<0.01	

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