Essays on the Various Aspects of Portfolio Flow in Emerging Markets

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Abstract

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The portfolio investment in emerging markets is two-sided. Increasing financial globalization in emerging market economies has helped to attract a large amount of non-resident portfolio flows, providing local economic agents with risk-sharing and external financing opportunities. However, greater exposure to foreign investments has made local financial markets more vulnerable to external and global shocks. Hence, policymakers in emerging countries should consider the diverse characteristics of portfolio flow to promote foreign investment while minimizing financial risks. In this paper, I examine some aspects of portfolio flows in emerging markets, which provide useful policy implications.

In the first chapter, I examine the herd behavior of the equity fund movement of small investors in emerging markets. By analyzing the international equity fund investment of fund managers in 20 emerging markets from 2003 to 2018, I find that a few large global investors dominate the equity fund markets and the movement of small investors' equity funds shows herding. To show evidence of herding, I use a panel regression model which improves the conventional method. I observe the relationship of equity fund investments between large and small investors in emerging markets and conclude that small investors tend to imitate the previous behavior of large investors, leading to herd behavior. Also, this tendency is

shown stronger particularly on extreme flows of small investors.

In the second chapter, I analyze the effect of tightening macroprudential policies on the volatility of investors' equity flows in emerging markets. To analyze the policy effect in an accurate and robust manner, I apply the double machine learning method with an investor-level dataset, mitigating problems such as reverse causality and omitted variable bias. As a consequence, it is shown that macroprudential policies contribute to stabilizing the fluctuation of equity flows in emerging markets. Particularly, I find that the smoothing effect of macroprudential policies is due to the dampening of the volatility on extreme flows. Moreover, tightening macroprudential policies are proven to be effective where they are less frequently used.

In the last chapter, I establish the sequential move model with strategic complementarities, in which a large investor moves first, followed by a continuum of small investors. Given these assumptions, small investors tend to follow the large investor's behavior, leading to herding. And the level of herding becomes higher as the dominance of the large investor increases.

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DEDICATION

To my dear wife, So Young and lovely son, Sehwan,
for their support,
for their love

Chapter 1

HERD BEHAVIOR IN THE EMERGING PORTFOLIO MARKETS: EVIDENCE FROM THE BEHAVIORS OF LARGE AND SMALL INVESTORS

1.1 Introduction

Herd behavior is often observed in the financial market. Investors observe others' behaviors and consider them as one of the critical factors when they determine their investment. In a financial market that is competitive and rapidly changing, investors tend to imitate others' investment decisions due to the lack of information or the reputation of the other investment institutions. This behavior tends to be strengthened as more investors follow the herding, and it can destabilize the market since herd behavior is occasionally against rational decision-making.

Herd behavior has been studied mainly focusing on the stock market in advanced economies. In empirical studies, they show different results depending on the sample of funds and period. Lakonishok et al. (1992) find little evidence of significant herding among pension fund managers in the U.S. stock market. On the other hand, Grinblatt et al. (1995) and Wermers (1999) conclude that the U.S. mutual funds exhibit a significant level of herding in some cases, such as buying past winners or small stocks. Wylie (2005) presents that the herding tendency of U.K. equity mutual funds is similar to that of U.S. mutual funds.

However, there has been little research on herd behavior in emerging market economies (hereafter referred to as EMEs) due to the lack of data. Choe et al. (1999) and Kim and Wei (2002) examine the herd behavior during the Asian financial crisis by using Korea's stock market trade data, and Zheng et al. (2021) analyze the herd behavior of individual investors in the Chinese stock market, but not much research about EMEs has been conducted compared with advanced countries. Considering the effect of herding on EMEs and their propagation, however, the importance of analyzing herd behavior in EMEs has grown. Especially in the portfolio markets of emerging countries, the herd behavior of investors is observed frequently. A sudden drop in portfolio flows is a good example. The striking outflow of non-resident institutional investors aggravates the uncertainty of emerging markets and encourages other investors to follow the same behavior. This herd behavior destabilizes the financial market in emerging countries and can lead to a financial crisis. Therefore, the herding of portfolio flow in the EMEs can propose new insight not only for the fluctuation of portfolio flow but for the business cycle of emerging countries.

The analysis of portfolio flow relies markedly on the institutional investors and hence their behaviors are very important to understand the herd behavior in the EMEs. As the cross-border portfolio flows have grown and the barriers have loosened over the decades, investment institutions have become crucial participants in the emerging financial market and they have had a significant influence on the market. Disaggregating by the investment size of the investors, there exists a large asymmetry among investors in the emerging financial market. Based on the investors' size distribution, investors are roughly grouped into two types - a few large investors and many small investors. It shows a large gap between the two groups not only in investment or firm size but in the information set, experience, and managing skills. This heterogeneity induces investors to rely more on others, leading to consider others' behavior in determining the investment. Particularly when a few large investors dominate the financial market, their behaviors can be a benchmark to the small investors and the market. Consequently, the dominant investors and interaction between large and small investors can cause herd behavior in emerging financial markets.

First, I examine the herd behavior of equity fund managers in the EMEs by using the EPFR (Emerging Portfolio Fund Research) Global dataset which provides investors' country allocation of equity funds. Applying the conventional methodology to measure the level of herding (Lakonishok et al., 1992), I find evidence of significant herding among small investors in the emerging equity markets, a phenomenon that became more evident after the global financial crisis. The average herding measure over the period is around 8 – 9 percent which is relatively high compared to previous literature (around 2 percent for Lakonishok et al. (1992); 4 – 5 percent for Grinblatt et al. (1995); 2 – 4 percent for Wermers (1999); 5 – 6 percent for Kim and Wei (2002); 4 – 5 percent for Zheng et al. (2021)), and it is particularly higher by 1 – 2 percent after the global financial crisis. Moreover, it presents a higher level of herding as the size of the investor decreases, and as the investment size of the country gets larger.

Despite evidence of the herding of small investors, the LSV method has some limitations. First, it can lead to biased results (Jurkatis, 2022; Frey et al., 2014; Bellando, 2010). Moreover, the LSV measure just shows the degree of dispersion of a particular group at the overall level, whatever the causes. Thus, it includes unintentional herding that accidentally shows a similar behavior facing an identical economic situation even if each investor does not intend to imitate others' behavior. In order to find robust evidence of herding, it is necessary to exclude unintended herding by controlling macroeconomic variables.

To correct the conventional LSV method and find evidence of herding in emerging markets, I run the panel regression controlling macroeconomic variables. In addition, I include the large investors' effect in the model since there exists empirical evidence that current small investors' equity investment is related to the previous large investors'. This observation is based on the characteristic of EPFR data which presents that the dominance of large investors has grown in emerging markets. I can find evidence of herding by observing that small investors tend to follow large investors' action simultaneously.

The panel regression covers 20 emerging countries from 2003 through 2018. The model is based on the view of fund managers' demand for investment, *á.la.* demand approach. This approach differs from most previous analyzes, which are based on a top-down approach by using aggregate flows, to help understand the behavior of investors such as herding. And I consider domestic economic fundamentals (e.g. interest rate, stock market index, total reserve, and GDP; pull factors) and external conditions (e.g. global risk premium, interest rate, and GDP of U.S.; push factors) as common macroeconomic controls. These factors are based on the previous literature examined when analyzing the drivers of capital flow (Hannan, 2017; Koepke, 2019). And the average growth rate of the 7 large investors in the previous period is included in the model as the effect of large investors.

The result of the panel regression indicates that the equity investment of small investors tends to follow the preceding equity investment of large investors. Considering the dominance of large investors in the market, the investment decision of large investors is regarded as the benchmark when small managers determine the equity investment, and hence small investors are likely to mimic the benchmark. Disaggregating by period, the influence of large investors is shown valid in pre- and post-crisis. These results show evidence of the herding of small investors in emerging markets.

It is noteworthy that small investors do not follow large ones during the GFC. In an unprecedented recession, tightening liquidity constraints forced small investors to make immediate investment decisions before observing the large investors' decisions. Also, the effect of large investors is more significant as the size of investors decreases. Overall, the top 10 percentile small investors do not consider the preceding investment of large investors in the investment decision. This is because smaller investors own less information and are influenced more by external conditions. They are more likely to rely on large investors who have much more information and dominate the market.

Furthermore, the large investors' effect becomes stronger for the extreme flows of small investors. For example, when the growth rate of equity funds is greater than 10% in absolute value, the large investors' effect is statistically significant with an expected sign. Conversely, it loses significance when the small funds' investment grows by less than 10%. Small fund managers seem to actively learn large funds' investment decisions only when they make a considerably large purchase or sales decision. These results call for close monitoring of large investors' transactions in the emerging equity markets to predict surges or sudden stops of foreign portfolio flows.

This chapter contributes to the previous studies in several ways. First, it shows the herd behavior of investors in emerging markets, which has not much been dealt with. And I find strong evidence for herding during non-crisis periods and the absence of herding during the GFC, complementing the earlier result of Choe et al. (1999). Second, I propose a new method to present herding to overcome the drawbacks of the conventional method by using investor-level data and controlling common macroeconomic variables. Furthermore, I introduce a demand approach method based on the investor-level analysis, which is different from most previous studies, to help analyze the investors' behaviors such as herding. Lastly, it sheds light on the importance of the large investors' role as Corsetti et al. (2004) show. It suggests policy implications for emerging countries that need to keep on watching the movement of large investors and manage their extreme volatility.

The rest of the paper proceeds as follows. Section 1.2 introduces related literature about herding and the role of the large player. Section 1.3 describes the dataset and provides relevant statistics about the portfolio flows in emerging markets. Section 1.4 measures mutual funds' herding among small investors by using the conventional method and presents the various aspects of herding. Section 1.5 shows the panel regression results to find evidence of herding among small investors in emerging equity markets. Section 1.6 concludes.

1.2 Related Literature

Herding is the tendency to follow others' behavior regardless of their own information as addressed in Scharfstein and Stein (1990); Banerjee (1992); Bikhchandani et al. (1992); Park and Sabourian (2011). There are two key features that describe herding - imitating the behavior of the crowd and herd behavior overwhelming the private information. As the action is strengthened by iteration, the agents tend to ignore their own information regardless of its value and are swamped by the others' observed actions. Hence, the herding can derive an inefficient outcome, leading to the destabilization of the market.

Some literature on herding (Bikhchandani and Sharma, 2001; Wermers, 1999) has presented several reasons for intentional herding. First, most studies (Banerjee, 1992; Bikhchandani et al., 1992; Avery and Zemsky, 1998; Park and Sabourian, 2011; Cipriani and Guarino, 2014) consider herding as an informational cascade. In other words, herd behavior can arise due to the information asymmetry among agents, which means that less-informed agents tend to follow better-informed agents. Also, consideration of reputation is another driver of herding. A high reputation of the leader or reputation risk of deviation from others' actions produces an incentive to mimic others' behavior (Scharfstein and Stein, 1990; Graham, 1999). Furthermore, the incentive mechanism for managers based on the comparison with the benchmark can induce herding (Maug and Naik, 1996).

Studies on herd behavior are divided into theoretical and empirical works in general. For the theoretical work, Banerjee (1992) and Bikhchandani et al. (1992) develop the model of herd behavior by introducing a sequential decision model. They exhibit that the agents imitate the decision of predecessors, ignoring their own private information as the same action iterates. Avery and Zemsky (1998) aggregate the price mechanism into the preceding model in order to analyze herd behavior in the financial market and they find the arise of herding in the presence of multiple dimensions of uncertainty.

Bikhchandani and Sharma (2001) summarize the research on herd behavior in the financial markets and organize the theory. They classify herding into two categories, unintentional (spurious) and intentional (true) herding, and introduce three types of herd behavior based on reason – information-based herding, reputation-based herding, and compensation-based herding.

Another branch of herding literature is finding empirical evidence that this paper mainly addresses. Lakonishok et al. (1992) develop the herding measure by calculating the dispersion of specific stock trade (the portion of stock purchase out of the total number of trading) from the overall average stock trade. It indicates stronger evidence of herd behavior as the value for the measure increases. By using this measure in the U.S. pension fund market, they conclude that there has little evidence of herding. This methodology has been widely used to measure the degree of herding in much literature. Grinblatt et al. (1995) find evidence of significant herding of the U.S. mutual funds when buying the past winners and trading with the herd. Wermers (1999) also observes stronger herding in small stock and in trading by growth-oriented mutual funds - a high degree of herding when buying the high past-return stocks and when selling the low past-return stocks. And Wylie (2005) shows that the herding in the U.K. equity mutual funds is similar to that in the U.S. mutual funds.

The works of Choe et al. (1999) and Kim and Wei (2002) are noteworthy in that they examine the herd behavior in the developing country by adopting the methodology to measure herding that had been used in the advanced economy. They use Korea's stock market data and compare the level of herding before the Asian financial crisis with during the crisis. Choe et al. (1999) find a high degree of herding before the economic crisis while herd behavior is withdrawn during the crisis period. On the other hand, Kim and Wei (2002) show the different results that nonresident institutional investors strengthen positive feedback trading during the crisis. And Zheng et al. (2021) find evidence of significant herding in the Chinese stock market, and the herding tendency of females is stronger than that of males.

Despite the simplicity and popularity of the LSV measure, it has limitations mentioned in previous studies. Jurkatis (2022) indicates the LSV measure can be biased and may not be consistent depending on the controls. Frey et al. (2014) and Bellando (2010) also show that it generates biased outcomes.

The attention to firm size and the asymmetry between large and small firms have been studied in many macro-research. Gertler and Gilchrist (1994) find empirical evidence that small firms are more vulnerable to tightening monetary policy than large firms. The two types of firms exhibit asymmetric behavior - small firms tend to decrease inventories rapidly while large firms initially borrow to increase inventories. Recently, Crouzet and Mehrotra (2020) also show asymmetry results between large and small firms that small firms experience more drop in sales corresponding to a contraction of GDP than large firms. However, the higher cyclicality of the small firms has restricted to affect the aggregate fluctuation due to the high and rising concentration of sales and investment to the large firms.

Gabaix (2011) highlights the importance of large firms in aggregate fluctuation. He finds the fat-tailed distribution of firm size, meaning substantial size difference between large and small firms. Given the distribution, idiosyncratic firm-level shocks to large firms (incompressible "grain") have a significant impact on the aggregate movement of GDP, which is called the "granular" hypothesis. This paper contributes to the business cycle studies by suggesting that microeconomic shocks at large firms propagate to aggregate macroeconomic fluctuation.

Corsetti et al. (2004) also shed light on the role of large traders in the financial market. The small traders become more aggressive in their trading strategy due to the presence of the large trades, leading to a currency crisis. In addition, the observed preceding trading position of large traders is recognized as a significant signal and hence it can affect more substantially the trading decision of small traders. However, the effect of large traders is restricted in the case of less well-informed large traders, which implies that the informational gap is the crucial factor that makes small traders act differently.

1.3 Data

1.3.1 The Emerging Portfolio Fund Research Dataset

The Emerging Portfolio Fund Research (EPFR) Global[1] dataset provides fund flows for emerging markets and country allocation of fund managers based on samples of self-reporting funds. The data consists of an equity fund and a bond fund, having a large number of data in an equity fund. Fund flows indicate each fund manager's inflow and outflow of globally domiciled ETFs and mutual funds daily, weekly, and monthly. And country allocation exhibits the monthly portfolio allocation of each fund manager to countries or regions, which is estimated by taking an average of monthly fund flows of the country-specific portfolio under simplifying assumptions such as no valuation changes. (Koepke and Paetzold, 2020)

EPFR data is widely used despite the caveats the dataset doesn't cover all types of emerging market fund managers. It provides high-frequency flow data compared to the other dataset such as IMF's Balance of Payment (BoP) data. Also, the dataset is constructed based on the fund manager level and hence is useful to analyze investors' behavior. Given that this paper examines herd behavior among investors, EPFR data is very suitable for the goal

[1] https://financialintelligence.informa.com/epfr

of the research. Moreover, the equity flows of emerging countries in EPFR including a large number of samples show a similar trend to that in BoP data representing the aggregate flows (Koepke and Paetzold, 2020). Therefore, the trend of aggregate equity flows can be predicted from the analysis of equity flows in EPFR data.

1.3.2 Data Construction

How to Construct Panel Dataset

Fund flows data and country allocation data are widely used in EPFR Global dataset. Fund flows data provides the inflows and outflows of particular mutual funds managed by institutional investors. And country allocation data presents the fund managers' portfolios allocating to countries. In this study, I use the country allocation data of equity fund managers rather than fund flows data since it has some missing points for the panel data consisting of every investor and 20 countries from 2003 to 2018. And I examine the equity funds without using the bond funds, considering the similar trend of equity funds in the EPFR dataset with the aggregate equity flows of BoP data. The number of observations of bond funds is much lower than that of equity funds which might lead to the inaccuracy of the analysis.

20 countries[2] are selected since the investment of equity funds to these 20 countries occupies a substantial proportion of whole emerging economies and these countries have the full set of macro variables[3] for the given time period. And the period, 2003–2018, is chosen considering the availability of the EPFR dataset and macro variables.

The observation of country allocation data consists of the total net assets and the allocation share (%) to each country per mutual fund managed by each institutional investor every month. First, for every mutual fund, I transform the share (%) of each country to the

[2] Brazil, Chile, China, Colombia, Czech Republic, Hungary, Indonesia, India, Israel, South Korea, Mexico, Malaysia, Peru, Philippines, Poland, Russia, Thailand, Turkey, Taiwan, South Africa

[3] short-term (3 month) interest rate, consumer price index, industrial production, total reserve, exchange rate, stock market index

size (mil. USD) of equity investment[4]. And then, I merge all kinds of mutual funds for each fund manager by every country and month to calculate the total size of equity investment for each investor. Small fund managers whose either size of total net assets or the number of observations is too small are dropped from the dataset[5] and thereby there are around 100 investors (76–127) per month. Finally, the panel dataset is constructed, consisting of time-varying fund managers (around 100), 192 months (2003.1 – 2018.12), and 20 countries.

How to Separate Large and Small Investors

The selection of large and small investors is an important work in this research to examine how the relationship between large and small investors affects equity flow in emerging markets. There are no definite rules to separate both investors, yet in general, the threshold of large firms relies on the distribution of the observations in the data. Gabaix (2011) supposes the 100 largest firms in Compustat as large firms by the previous year's sales. Gertler and Gilchrist (1994) divide into large and small firms based on the thirtieth percentile of sales while Crouzet and Mehrotra (2020) establish the cutoff as the 1 percent by size. Based on the size distribution of investors in the EPFR dataset, I define the large investor as the top 7 fund managers[6] by total net assets and the remaining managers as the small investors. The large investors have been the 7 largest investors across the period and there exists a large gap in size between these investors and the remaining ones.

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[4]The size of equity investment to a particular country = The total net assets × The allocation share of the country

e.g. 2011.12. JP Morgan Asset Management (Total net assets) \$ 8825.826 mil for Global Emerging Market Fund and (Allocation to South Korea) 10.07% $\Longrightarrow$ (Size of equity investment to South Korea for Global Emerging Market Fund) 8825.826 ×10.07% = \$ 888.76 mil

[5]Precisely, we drop observations if their observations are smaller than one year (12 months), or if their over-time average total investment is less than USD 100 million.

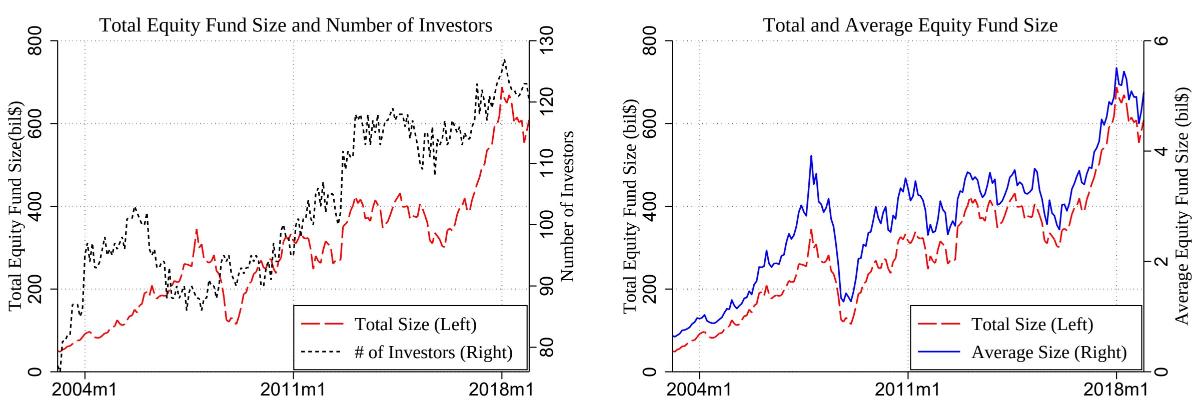
[6]BlackRock, Capital Research & Management, Franklin Templeton Investment Management, Genesis Investment Management, JPMorgan Asset Management, Schroder Investment Management, Vanguard Group

1.3.3 Data Statistics

Overall Trend of Equity Funds

Figure 1.1 shows the overall trend of equity funds investments in the EPFR data. The total size of equity funds to 20 emerging countries has grown from 50 to 600 billion US dollars despite a sharp drop in 2008 as shown in the red dashed line of the left panel. And the number of investors indicates a similar trend with total equity funds size, increasing from 76 to 125. It implies that the equity funds markets in emerging countries have expanded over the period.

Figure 1.1: Trend of Equity Funds Size and Number of Investors



The average equity funds size[7] which is shown in the blue line of the right panel also exhibits quite the same trend as total equity funds investments, with quadrupled increment over the period. Both the trends of total and average equity funds describe a sudden fall in 2008 and a sharp rise in recent.

[7] Average equity funds size = Total equity funds size / Number of investors

Large and Small Investors

Disaggregating the EPFR data by investors' size, it presents that the equity funds investments size increase exponentially as the size of the investor grows. Table 1.1 proposes that the average equity funds size of the 7 largest investors is around 20 times that of the other investors. Among small investors, the average investment size expands dramatically as the percentile of investors' size increases, too.

Moreover, the average investment gap between large and small investors has been enlarged from 11 times to 20 times over the period. I find the asymmetry of investment growth among the fund managers – the average investment of large investors has been much more than tripled during the period while that of small managers has been less than doubled. Especially, the small investors that are below the 75 percentile of the size increase slightly or even decrease their equity funds investments to EMEs. The asymmetry makes the gap between large and small investors bigger over time.

Table 1.1: Average Equity Funds Investments Size by Investor

	All	Pre GFC	GFC	Post GFC
All Investors	2856.0	1416.9	2465.1	3468.2
	(104.7)	(93.2)	(90.5)	(111.5)
Large Investors	23937.0	8949.6	16241.9	32319.9
	(7)	(7)	(7)	(7)
Small Investors	1322.6	802.2	1308.4	1519.7
	(97.8)	(86.3)	(83.5)	(104.6)
> 90th	6342.5	3457.0	5269.3	7630.7
	(11.0)	(9.9)	(9.6)	(11.7)
75 - 90th	2148.7	1283.9	2308.8	2451.4
	(15.8)	(14.1)	(13.6)	(16.8)
50 - 75th	761.9	535.2	901.5	823.8
	(26.3)	(23.4)	(22.8)	(28.0)
0 - 50th	115.7	112.6	170.5	107.9
	(44.8)	(38.9)	(37.4)	(48.1)

mil US$; average number of investors in parentheses

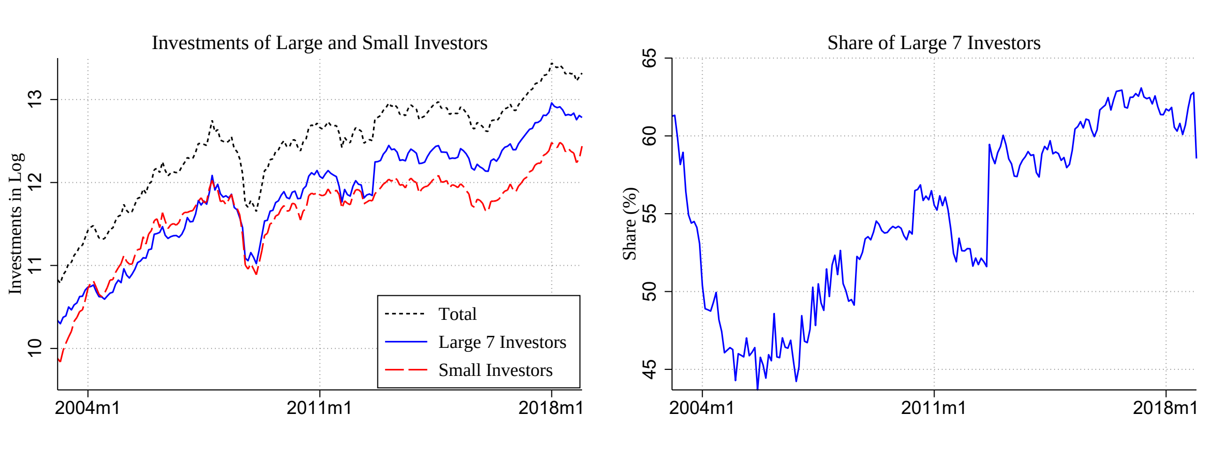


Figure 1.2: Trend of Equity Investment for Large Investors

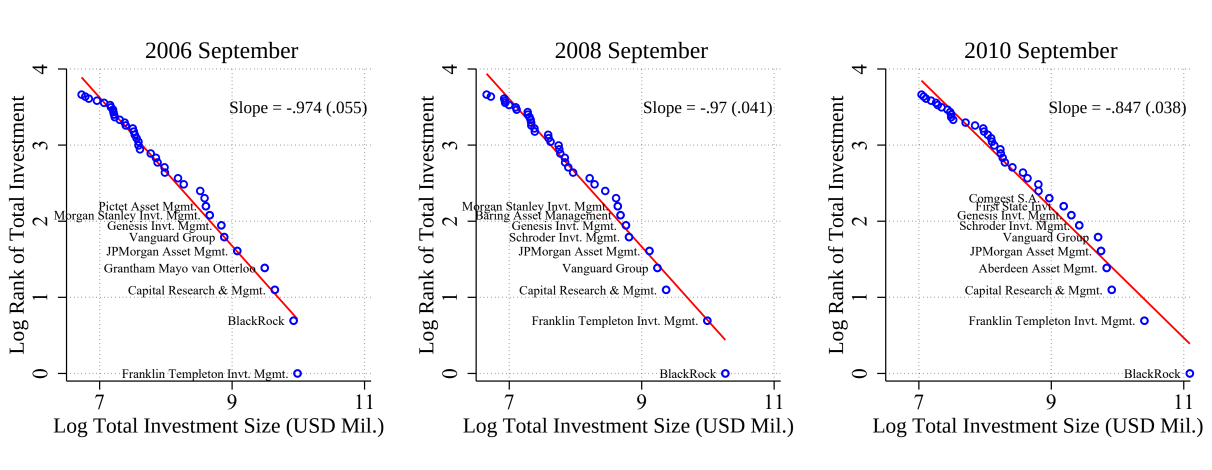
Figure 1.2 indicates that large investors have dominated across the period. In the left panel of the figure, the equity investment of the 7 largest investors (blue line) exceeds the other small investors (red dashed line), and the gap between the two groups gets bigger. The share of the large investors has grown from 45 to 60% out of total equity funds investments as shown in the right graph of Figure 1.2. From the data, it can be inferred that the disparity between large and small managers has been expanding and it makes the equity fund market in EMEs depend more on large investors.

This observed concentration can be verified by looking at the distribution of mutual funds' equity investments. Figure 1.3 shows a fat right-tail of size distribution before, during, and after the GFC, implying that investors are grouped by a few large investors and a number of small ones. The total investment grows exponentially as the rank of investors' size is higher. In the figure, the slope of prediction is linear, which implies the power law. Especially, the absolute value of the estimated slope is close to one, which implies Zipf's law[8].

[8] Zipf's law is an empirical rank-frequency distribution that has a heavy tail. Gabaix (1999) applies Zipf's law to the size distribution of cities strikingly fitting a power law – the number of cities with populations larger than S is proportional to $1/S$.

$$P(\text{Size} > S) = \alpha / S^{\xi}$$

Figure 1.3: The Right Tail of Investor Sizes



Notes: The figures plot the 40 largest investors' logged rank of total investment and logged total investment size in 20 emerging equity markets in September 2006, 2008, and 2010 (pre-, during-, and post-global financial crisis). The robust standard errors of slope estimates are in parentheses. The absolute value of the slope of predictions (red line) implies the coefficients of power distribution.

The Other Statistics

EPFR Global dataset distinguishes actively and passively managed fund flows. Passive funds, also known as a passive index or index-style funds, automatically replicate a market index such as S&P 500 or FTSE 100 in the composition of stocks and thus match the performance of the index. Active funds consist of their own portfolio of stocks constructed directly by the fund managers, and thus they can perform better or worse than the market.

Figure 1.4 exhibits the trend of active and passive equity funds over the given period. In the first panel, the investment in passive funds has increased more sharply than that in active funds. The size of passive funds exceeds that of active funds after 2015 while active funds stay relatively stable. This trend is due to the substantial increase in the investment

And it finds that the slope of the curve($-\xi$) is close to -1

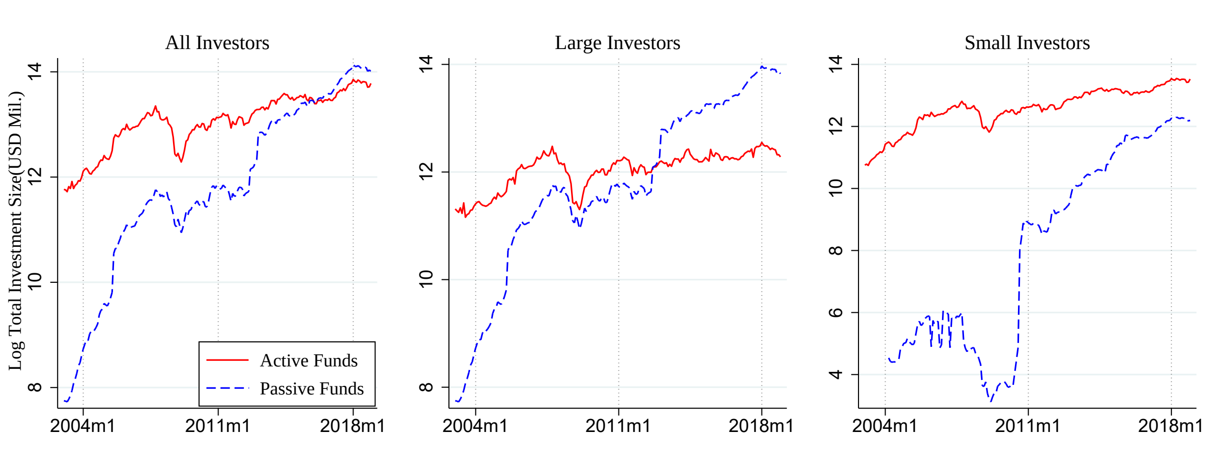


Figure 1.4: Trend of Equity Investment for Active and Passive Funds

of large investors in passive funds as shown in the second panel. Comparing the second panel with the third one, the investment size of passive funds shows a similar level to active funds after the global financial crisis in 2008 and even exceeds that of active funds after 2012. This is in contrast to the fact that small investors invest in active funds more than passive funds over the period notwithstanding the increase in the investment in passive funds recently. It is inferred that the rise of passive funds investment is led by large investors and small investors follow the trend. Large investors have increased the portion of passive funds to reduce the financial risk that arises from establishing the portfolio with a hands-on approach, and then small investors appear to follow these large investors' strategic behaviors. Meanwhile, the amount of active funds investment does not show a significant change during the given period for large and small investors.

Furthermore, the investors' equity investments in the dataset can be classified at the country level. Examining by country, investors put a much different weight on each emerging country when investing in equity funds. Table 1.2 presents a large disparity of investments among emerging markets. The equity funds investments are concentrated in a few countries - Brazil, China, India, South Korea, Russia, and Taiwan - which consist of over 72% of total investment. These countries have higher GDPs and better financial markets than other emerging countries, implying that equity investment of fund managers depends on the size of the economy and the degree of development of the financial market. This trend has continued over the period, with increasing equity funds investments.

Table 1.2: Average Equity Funds Investments Size by Country

	BRA	CHL	CHN	COL	CZE	HUN	IDN	IND	ISR	KOR
Pre GFC	15114	1377	12502	153	1638	3193	2830	8404	2109	23808
(03.2-07.5)	(8236)	(354)	(9671)	(123)	(508)	(1149)	(1051)	(2792)	(965)	(7220)
GFC	33659	2171	40427	357	2101	2565	4329	15850	3599	25409
(07.6-09.5)	(10233)	(265)	(12110)	(99)	(599)	(1363)	(1560)	(5030)	(577)	(10000)
Post GFC	44246	4848	89048	1548	1135	1824	10136	40063	3863	45722
(09.6-18.12)	(11129)	(1149)	(44092)	(702)	(330)	(548)	(2697)	(14914)	(1870)	(16600)
All	34984	3567	62099	1019	1393	2289	7418	28401	3352	37203
	(16291)	(1840)	(48800)	(855)	(546)	(1060)	(4049)	(18715)	(1725)	(17379)
	MEX	**MYS**	**PER**	**PHL**	**POL**	**RUS**	**THA**	**TUR**	**TWN**	**ZAF**
Pre GFC	9202	3381	234	841	3291	13362	3520	3785	14776	7927
(03.2-07.5)	(2900)	(1157)	(99)	(467)	(1320)	(8513)	(1289)	(2134)	(6506)	(3084)
GFC	12221	4391	787	1666	4062	25632	5522	6180	21510	10344
(07.6-09.5)	(3389)	(1696)	(184)	(632)	(1812)	(11918)	(1759)	(2354)	(6281)	(2372)
Post GFC	16405	8577	2059	4910	4604	22151	13476	7489	40222	21439
(09.6-18.12)	(2633)	(2918)	(502)	(2131)	(1049)	(5380)	(4179)	(1934)	(17238)	(7394)
All	13918	6637	1402	3395	4178	20196	9766	6316	30943	16366
	(4243)	(3411)	(917)	(2527)	(1361)	(8535)	(5708)	(2593)	(18147)	(8699)

mil US$; standard deviation in parentheses

1.4 Herd Behavior in Emerging Equity Markets Based on Conventional Method

1.4.1 Conventional Herding Measure

LSV measure of herding

Herding is a phenomenon in which a group of agents exhibits identical behavior in the market. If there exists herding in the market, the tendency of a specific behavior in the group significantly deviates from the level when agents choose that behavior randomly and independently. Lakonishok et al. (1992) construct the measure of herding given this point. The LSV measure of herding, extensively used in the finance and economics literature, assumes that traders choose to buy or sell the stock at each period in the market. And the decision whether to buy or sell is the outcome of a Bernoulli trial with a probability of $p_{i,t}$, which is the propensity to buy a stock i at time t. In case of no herding, each trial is independent of other trials. In other words, there exists no herding under the null hypothesis, $H_0 : p_{i,t} = p_t$, where p_t is the average of $p_{i,t}$ over the stock i at time t. On the contrary, the greater the difference between $p_{i,t}$ and p_t, the more there is a tendency to herd. Based on this setting, the LSV herding measure, $H_{i,t}$, is defined as:

$$H_{i,t} = |p_{i,t} - p_t| - AF_{i,t} \tag{1.1}$$

$$p_{i,t} = \frac{B_{i,t}}{N_{i,t}} \tag{1.2}$$

$$AF_{i,t} = E[|p_{i,t} - p_t|] \tag{1.3}$$

where $B_{i,t}$ and $S_{i,t}$ are the number of traders who buy and sell a stock i at time t, respectively. The number of participated traders of stock i at time t is $N_{i,t} = B_{i,t} + S_{i,t}$. The first term of $H_{i,t}$, $|p_{i,t} - p_t|$, indicates the absolute value of the deviation of buying ratio of stock i from the overall level of buying ratio. The higher the first term is, the more likely there exists herding. And the second term, $AF_{i,t}$ is the expected value of the first term, $|p_{i,t} - p_t|$, under the null hypothesis of no herding ($H_0 : p_{i,t} = p_t$). It means that the second term is driven by the assumption that $B_{i,t}$ is randomly drawn from a binomial distribution with a probability of $p_{i,t}(=p_t)$ and dimension $N_{i,t}$ as follow:

$$AF_{i,t} = \sum_{k=1}^{N_{i,t}} \binom{N_{i,t}}{k} p_t^k (1-p_t)^{N_{i,t}-k} \left| \frac{k}{N_{i,t}} - p_t \right| \tag{1.4}$$

The reason why the adjustment factor is included is that the first term in the right-hand side of equation 1.1, $|p_{i,t} - p_t|$, is greater than zero even under the null hypothesis of no herding (Wylie, 2005; Voronkova and Bohl, 2005). This is because of restrictions on short sales and the different sizes of traders each period. First, the number of sales is constrained depending on the position if short sales are not allowed. This restriction makes a left-truncated distribution, leading to an overestimation. Second, $p_{i,t}$ is influenced by the number of traders, $N_{i,t}$, in which a low number of traders can lead to a bias. Therefore, introducing the adjustment factor, $AF_{i,t}$, makes the LSV measures equal to zero under the null hypothesis of no herding. Finally, the overall LSV herding measure, H_t, is the average of the measures, $H_{i,t}$, over the stock.

Application of LSV measure to EPFR dataset

In this chapter, I

I redefine the variables to fit EPFR data while retaining the basic setting of the LSV herding measure. I assume that fund managers choose to increase or decrease equity investments compared to the previous period in each country. Then, $B_{i,t}$ and $S_{i,t}$ are the number of fund managers who raise and reduce the equity investment of country i at time t, respectively. And $p_{i,t}$ is the propensity to increase the equity investment to the country i, and p_t is the average of $p_{i,t}$ over all 20 emerging equity markets at time t. Lastly, the herding measure, $H_{i,t}$, is calculated by using the same formula in the equation 1.1.

Furthermore, I measure the LSV herding value only for the active equity funds in gauging the level of herd behavior among small investors. The equity funds in the EPFR dataset are separated by actively and passively managed funds. Active funds choose their own portfolio by fund managers while passive funds (or index funds) replicate the movement of the market in the composition of stocks such as S&P 500 or FTSE 100 and match the performance of the index. To measure the exact level of herding, therefore, passive funds that are implemented without managers' portfolio decisions should be excluded.[9]

1.4.2 Empirical Evidence of Herding

Overall Trend

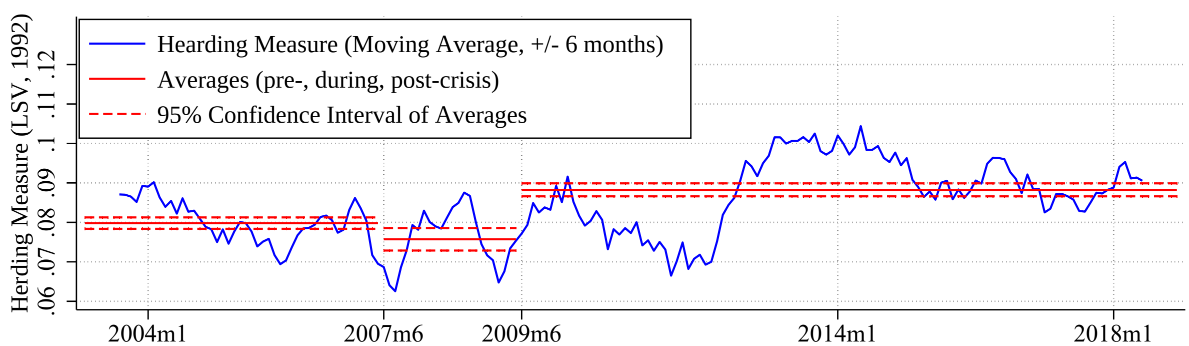


Figure 1.5: Trend of Herding Measure

Notes: The figure plots the herding measure supposed by Lakonishok et al. (1992). The blue solid line is the moving average of LSV measure, H_t, with $\pm$ 6 months to remove seasonality. The red solid line is the overtime average of LSV measure in each period (the pre-GFC, GFC, and post-GFC periods are 2003.2–2007.6, 2007.7–2009.5, and 2009.6–2018.12, respectively.), and the red dashed lines are corresponding 95% confidence interval.

Figure 1.5 presents the average LSV herding measure of emerging markets over time.[10]

[9] A higher level of herd behavior is shown when measuring for all the equity funds including passive funds as in Appendix A.

[10] The herding measure is calculated only considering the active funds. With a slight upward shift, it still

In the graph, the moving average with 13 months window (plus and minus six months) which is plotted in the blue line is provided to remove seasonality.

I find some important facts in the graph. First, there exists a significant level of herding. The LSV measure is statistically positive, meaning the existence of herd behavior. The measured value is around 9 percent, which is relatively high compared to the values of previous literature[11] The high level of LSV measure may come from two different sources. First, I use country-level aggregates instead of individual equities. Second, the previous studies focus on investors' herd behavior within the country, but this research is interested in portfolio choices across countries.

Moreover, herd behavior is differentiated across periods. Ahmed and Zlate (2014) and Ahmed et al. (2017) document significant changes in the behavior of aggregate net inflows from the period before the recent global financial crisis to the post-crisis period, especially for portfolio inflows. This result is consistent with the individual investors' behavior. The average herding measures diminish until the global financial crisis and rebound after the crisis. Particularly, a high level of herding is observed recently. Taking the average over each period, we find the LSV measure during the crisis is less than the other periods by 1–2 percent points.

Why does it show the low level of herding during the global financial crisis? During a crisis when the liquidity is extremely constrained, investors might withdraw investment because of the financial constraint regardless of others' investment decisions. In other words, investors put more emphasis on their internal financial status than external conditions in determining investment during the crisis, leading to a lower level of herding. This result is in line with the empirical finding of Choe et al. (1999) that herd behavior shrinks during the Korean currency crisis in 1997.

Also, it might be due to a statistical problem. Under a few observations, it is hard to

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shows a quite similar trend when including both active and passive funds.

[11] The average value of LSV measure in the previous empirical literature is around 2–5% for the advanced economy (Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999; Wylie, 2005) and 4–6% for emerging economies (Kim and Wei, 2002; Zheng et al., 2021).

test whether herd behavior is observed. The number of time observations during the crisis is just 24, which is much lower than the other periods (53 for the pre-crisis period, 114 for the post-crisis period). It causes a relatively wide confidence level of average during the crisis seen in Figure 1.5. The sample number during the crisis might not be enough to confirm whether there is herd behavior in the market. Thus, we leave these issues —heard behavior during the crisis— open for future research.

Herding by Investor's Size

Table 1.3: Average Herding Measure by Investor's Size

		Sub-Period			All Period
		Pre GFC	GFC	Post GFC	
Large Investors		4.42	3.84	5.65	5.09
Small Investors	Total	8.05	7.50	8.90	8.53
	90–100th Percentile	5.67	4.38	5.65	5.51
	75–89th Percentile	4.64	5.17	6.20	5.69
	0–74th Percentile	6.71	5.96	7.49	7.12

Notes: 1. Presented in the table are values of H_t averaged of herding measure, H_{it}, across all countries for the given periods and groups. For example, the value of H_t shown in the first row, second column, is the average of H_{it} of 20 countries for 7 large investors during the pre-global financial crisis. The pre-GFC, GFC, and post-GFC periods are 2003.2–2007.6, 2007.7–2009.5, and 2009.6–2018.12, respectively. Small investors are grouped by size distribution. For example, the fourth row, 75–89th, means small investors whose equity investment is between 75 and 89 percentile of the size distribution.
2. The herding measure is calculated only considering the active funds. The table for the average LSV herding measure when including all the funds is exhibited in Appendix A.

Table 1.3 presents the average LSV herding measure by investors' size. The average measure H_t is taken as an average of H_{it} across all countries for given periods and subgroups. For a given subgroup, the herding measure H_{it} is calculated within the group. In other words, p_{it}, p_t, and AF_{it} in equation (1.1) are computed based on the investors only in the subgroup, not including the other investors.

First, we can find evidence of herding among investors in Table 1.3. The LSV measures are around 4–5 and 5–8 percent for large and small investors, respectively. These values imply a significant level of herding considering the previous literature as mentioned above. Also, we can find that the level of herd behavior is exhibited relatively low during the global financial crisis while high after the crisis as in Figure 1.5.

Disaggregating the herding measure by period and size, it provides some intriguing facts. First, small investors are more likely to herd than large investors. It implies that small investors are more affected by other investors. Large investors are not much influenced by the crowd due to plentiful information and dominance over the market. Rather, they determine investment based on their own information and belief about economic situations. However, small investors inevitably consider the investment decisions of others, especially large investors, as a critical factor since they may face a lack of information or the market is sometimes led by large investors.

For small investors, Table 1.3 generally shows evidence of a higher level of herding as the investors' size decreases. Except for pre-crisis, the top 10 percentile small investors exhibit relatively low herding while the herding measure of the bottom 75 percentile is high. Particularly, the bottom 75 percentile small investors tend to herd significantly over all the periods. As the investor gets smaller, they are likely to have less information and a lower level of managing ability, leading to relying more on other investors.

1.4.3 Limitations of the Conventional Herding Measure

Despite its simplicity and popularity, the LSV measure has some limitations. First, the LSV measure is biased depending on the fund level and the number of samples. The value tends to be overestimated as the fund level is more comprehensive (e.g. country level fund) and as the number of transactions or investors is smaller. Moreover, some studies (Jurkatis, 2022; Frey et al., 2014) show that it generates a biased estimator compared to the simulation results. Second, it tells only the degree of deviation from the average level regardless of the background of the herding. It includes unintentional herding (or spurious herding) that occurs when investors make similar decisions in similar economic conditions, even if they do not consider the behavior of other investors. Thus, the LSV measure can be overestimated compared to the real level of herding. In order to accurately measure the herding, however, unintentional herding should be excluded by controlling macroeconomic variables.

To find more robust evidence of herding, a new methodology is necessary. I find a clue for the method from the characteristic of data, which is that the presence of large investors plays an important role in the herd behavior of small investors.

1.5 Evidence of Herding by Using Panel Regression Method

In this section, I propose a new method to show robust evidence of herding. To correct the conventional LSV method in the previous section, I run the regression controlling macroeconomic variables. Particularly, I focus on the herd behavior among small investors by observing the characteristics of data – an asymmetry in size between few large investors and many small investors.

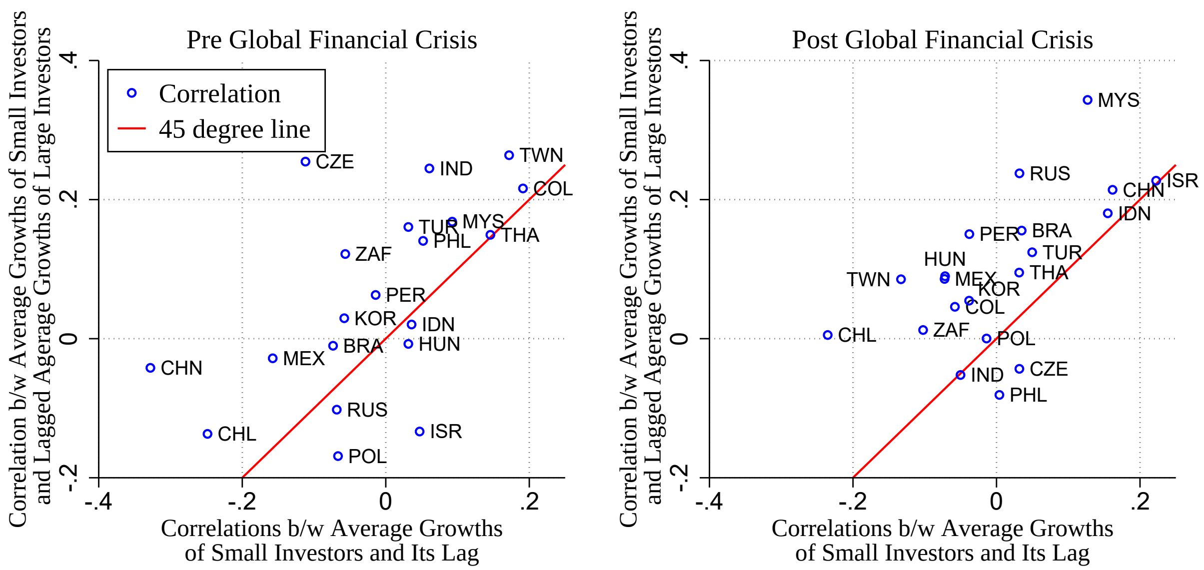
1.5.1 Descriptive Evidence

There might have some reasons for herding. Investors can follow others' investment decisions due to the lack of information or the reputation of some major investors. And this herding can arise more often in emerging markets that are more uncertain and volatile. Among the possible causes, I focus on the relationship between large and small investors in emerging markets. In Section 1.3, it is shown that the market consists of a few dominant investors and a number of small investors. Large investors play a key role in the market and their portfolio decision can be a benchmark for other small investors.

Based on the observation of the dataset, it is necessary to find empirical evidence that small investors consider the prior investment trend of large investors. Examining the equity investment relationship between large and small investors, I find evidence that small investors are considering the equity fund trend of large investors in the past. First, I calculate the correlation of the growth rate of small investors' equity investment between the current period t and the previous period $t-1$ ($=\text{corr}(g_{St},\, g_{S(t-1)})$) and the correlation between the growth rate of small investors' equity investment at t and that of large investors' one at $t-1$ ($=$

corr(g_{St}, $g_{L(t-1)}$)), and then compare them. This is because small investors consider not only the effect of large investors but also previous their own equity investment as a benchmark.

Figure 1.6: Correlation of Equity Funds Growth between the Current and Its Lag



Notes: The figures plot how small investors' equity flow is correlated with its own lag and large investors' lagged flow in each emerging market. The x– and y–axes are the correlations of $\overline{\Delta s_t}$ with $\overline{\Delta s_{t-1}}$ and $\overline{\Delta l_{t-1}}$, respectively, where $\overline{\Delta l_t}$ and $\overline{\Delta s_t}$ are the average growth rate of equity flows of the 7 largest investors (large investors) and the rest investors (small investors) at time t. The Pre- and Post-GFC periods are 2003.2–2007.6 and 2009.6–2018.12, respectively.

Figure 1.6 shows two correlations - the average corr(g_{St}, $g_{S(t-1)}$) on the horizontal axis and the average corr(g_{St}, $g_{L(t-1)}$) on the vertical axis. It shows that the current equity flow of the small investors has more correlation with the previous flow of the large investors than that of the small ones as the point gets closer to the vertical axis, and vice versa. In both graphs in Figure 1.6, most of the points are located in the upper-left of the red 45-degree line for both pre- and post-global financial crisis, implying that, in most countries, the current equity investment decisions of small managers depend more on the previous equity investment of large investors rather than that of small investors. And this trend appears more strikingly after the global financial crisis.

I find evidence of a link between the tendency of small investors to follow the large investors' decisions and herd behavior through Figure 1.6. The herding among small investors might occur since large investors tend to lead small ones. This hypothesis is consistent with the fact that, after the crisis, the equity flow of small investors exhibits more correlation with the previous flow of large investors in Figure 1.6.

1.5.2 Panel Regression Method

Taking into account the empirical fact, I test the hypothesis that small investors tend to follow large investors. For the model, the demand estimation approach is used to examine the effect of large investors in view of small investors. I construct the panel regression model for the movement of equity funds flow of each small fund manager that focuses on the effect of the behavior of large investors, controlling the related macro variables[12].

Capital flows, including portfolio flows, have been analyzed in the context of the business cycle using aggregate flows rather than examining the investors' flows in most of the previous literature. Despite the advantage of being able to outline overall, it is difficult to comprehend beyond the movement of aggregate flows, e.g. the detailed movement of each fund manager, or the interaction between managers. As institutional investors have recently played a critical role in emerging markets, however, understanding their portfolio choice becomes critical to analyze the capital flows considering their influences on the aggregate flows. Moreover, in order to examine the interaction between investors, which can affect the movement of flows,

[12]I set up a linear panel regression that shows the effect of large investors' behaviors and other macroeconomic factors on the dependent variable, the growth rate of equity fund investments to each country of each fund manager. This is the problem of how much a fund manager's investment in equity funds of a particular country is affected by the given regressors. Meanwhile, I also run the multinomial logistic regression model to test which factors affect the portfolio choice of fund managers in Appendix D. This is the problem of which regressors encourage a fund manager to invest in a particular country more than the other countries. I choose a linear regression model for the analysis of the movement of equity funds in emerging markets since it can use more information, not only the preference of a particular country over the others but also the growth rate of equity investments, than the multinomial logistic regression model. The result of the multinomial logistic regression model is introduced in Appendix D.

a demand approach based on investor level is essential rather than the previous methodology.

To establish the model, several assumptions are needed for simplification. First, I suppose each investor considers the total stock market of each emerging market as one equity. And investors determine whether to increase or decrease the equity investment size in each market by considering the characteristics of each equity. The characteristics of each equity are closely related to the economic conditions of the country. I include macroeconomic variables as characteristics of the country, which are used to analyze the determinants of capital flows in previous literature (Ahmed and Zlate, 2014; Ghosh et al., 2014; Hannan, 2017; Koepke, 2019). There are two kinds of variables to determine the flows - pull and push factors. The pull factor is a domestic feature that reflects the economic fundamental of the country (i.e. GDP growth rate, interest rate, and stock market index of the country). The push factor is external conditions that underpin the supply of global liquidity (i.e. global risk premium, GDP growth rate, and interest rate of the advanced economy). These pull and push factors are used as a proxy for the characteristics of each equity.

Adding to the base model, the large investors' effect, which identifies the relationship between large and small investors, is included. Given the correlation between large and small investors' investment decisions as shown in Figure 1.6, the observed previous equity investment of large investors should be considered as one of the critical factors in determining their investment. I calculated the average growth rate of equity investment for large investors in the previous period[13] and include it as a proxy for the effect of large investors. Also, I add the average growth rate of investment for small investors in the previous period as a proxy for the effect of small investors. This is for a robust check if the herd behavior of small investors results only from the effect of large investors or not. In other words, this tendency might just come from the fact that small investors follow others' behavior regardless of their size, and hence it is necessary to identify the sole effect of large investors by controlling the effect of small ones. We can find strong evidence that small investors tend to follow large

[13] $\overline{\Delta l_{c,t-1}} = \frac{1}{7}\sum_{i=1}^{7}[\ln(\text{equity}_{ic,t-1}) - \ln(\text{equity}_{ic,t-2})]$ where $e_{ic,t}$ is the equity investment of the large investor i to the country c in time t.

investors provided only the effect of large investors is significant. Furthermore, there exist unobserved heterogeneities of investors and countries that are not captured by pull and push factors, and hence these heterogeneities should be controlled as latent variables.

Motivated by the model in Chapter 3 and the previous empirical literature, I establish the panel regression model to test the hypothesis that small investors tend to follow large investors as follows:

$$\begin{aligned} y_{ic,t} =& \beta_L \overline{\Delta l_{c,t-1}} + \beta_S \overline{\Delta s_{c,t-1}} + \boldsymbol{\beta}_{pull} \mathbf{pull}_{c,t} + \boldsymbol{\beta}_{push} \mathbf{push}_t \\ &+ \xi_i + \xi_c + \xi_m + \epsilon_{ic,t} \end{aligned} \tag{1.5}$$

where i,c, and t index the investor, country, and time, respectively. The dependent variable $y_{ic,t}$ is the monthly growth rate (%) of equity investment of investor i for emerging country c at time t. Our main interests are $\overline{\Delta l_{c,t-1}}$ and $\overline{\Delta s_{c,t-1}}$ – the growth rate (%) of the average equity investment of large and small investors in the previous period, respectively[14]. $\mathbf{pull}_{c,t}$ (pull factor) includes the real interest rate, the growth rate of industrial production, the growth rate of the total reserve, the growth rate of the exchange rate, and the growth rate of the stock market index for each emerging country c while **push** (push factor) involves U.S. real interest rate, the growth rate of VIX, the growth rate of U.S. industrial production, and growth rate of U.S. stock market index (Dow Jones Industrial Average) are used for push factors.

To control unobserved heterogeneity of investors and emerging markets, the fixed effects are included[15]. ξ_i and ξ_c are latent variables to control individual investor-specific effects and country-specific characteristics, respectively. Finally, ξ_m is to control months (11 dummies) for removing the seasonality.

And as in Section 1.4, I use the equity investment of small investors for only active funds,

[14] I winsorize an individual investor's growth rate at the top and bottom 1% before calculating the large and small investors' average to remove the effects of outliers.

[15] Fixed effect estimator is consistent since it demeans both the dependent and independent variables so that removes the effect of unobserved heterogeneity (Gormley and Matsa, 2014).

not including passive funds, in order to measure the precise effect of how small investors' investment decisions are affected by the preceding decisions of large investors[16].

1.5.3 Empirical Result

Main Finding

Table 1.4 represents the result of the panel regression model 1.5. It shows that the average growth rate of the large investors' equity investment in the previous period has a positive impact on the current equity investment of small investors regardless of the fixed effects or pull/push factors. Specifically, the equity investments of small investors increase by 0.1% on average as large investors increase the equity funds by 1% in the previous month. That is, small investors tend to follow large investors significantly. Furthermore, this hypothesis is strengthened by the fact that the previous equity funds flow of small investors does not affect the current investment decisions. This is because it implies that small fund managers consider only the investment decision of large managers, not that of small investors. This is consistent with Figure 1.6 that small investors put more weight on the previous movement of large investors than that of small investors in determining equity fund investments in emerging markets.

There might have several reasons for the imitation of small investors. Bikhchandani and Sharma (2001) propose three causes for herding - informational cascade, reputation, and compensation. First, small investors confront a lack of information in investment decisions and hence they follow the observable fund flows of large investors who have an advantage of the information set. Moreover, they weigh on the trend of dominant players' investments since their movements have an influence on the aggregate fund flow and the emerging market. As an important signal to predict the market, small investors tend to follow the large fund managers to lessen the risk.

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[16] The regression results when including all equity funds show a similar trend. Appendix C provides the result tables of panel regressions (Table 1.4, 1.5, 1.6, 1.7, 1.8) for all equity funds.

Table 1.4: Panel Regression Result - Large/Small Investors' Effect

	(1)	(2)	(3)	(4)
Large Investors' Effect (%)	0.124***	0.092**	0.124***	0.096***
	(0.037)	(0.034)	(0.036)	(0.032)
Small Investors' Effect (%)	-0.049	-0.073	-0.051	-0.072
	(0.062)	(0.062)	(0.061)	(0.061)
Pull/Push Factors	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	335620	334687	335620	334687
R-squared	0.943	0.943	0.943	0.943

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. All regressions include the log of previous equity investment, and the coefficients of the other variables are omitted in the table to focus on the large investors' effect. The interpretation of the other variables is explained in Section 1.5.3.

Small investors might also mimic the behavior of large investors due to their reputation. Large investors generally have shown greater performance than small managers, which leads small ones to follow big ones based on the belief of better profits. Moreover, this tendency is intensified provided that the structure of compensation depends on the comparison of the other's performance. Investors are likely to imitate others' investment decisions, especially large investors' behaviors, regardless of private information to prevent the big loss that happened by not following the herd.

Disaggregating the large investors' effect by periods, the tendency that small investors follow large ones is observed throughout the period except during the crisis. Table 1.5 presents the co-movement of the equity funds flow of small investors with that of large fund managers in the previous period while the small investors' effect is not significant over the period. Small investors increase their equity investment by 0.12 – 0.14% as the previous equity investment of large investors rises by 1%, which is slightly higher than the overall effect, 0.1%. During the global financial crisis, however, large investors' effect is not significant. It can be explained by liquidity constraints or a relatively small number of samples as mentioned in Chapter 1.4. During the crisis, small investors might reduce their equity investment instantly without observing the behavior of large investors due to the liquidity constraint. Also, the number of samples during the crisis might be not enough to test if small investors tend to follow large investors. Given these reasons, I address the pre- and post-global financial crisis in which the effect of large investors on small ones is valid.

Table 1.5: Large/Small Investors' Effect by Period

	(1)	(2)	(3)	(4)	(5)	(6)
Large Investors' Effect (%)	0.123**	0.143**	-0.096	-0.102	0.125**	0.119***
	(0.058)	(0.050)	(0.058)	(0.060)	(0.048)	(0.042)
Small Investors' Effect (%)	0.075	0.024	-0.064	-0.004	-0.122	-0.103
	(0.095)	(0.097)	(0.133)	(0.126)	(0.079)	(0.071)
Period	Pre GFC	Pre GFC	GFC	GFC	Post GFC	Post GFC
Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	84100	84100	38240	38240	212347	212347
R-squared	0.940	0.941	0.916	0.918	0.948	0.949

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. The pre-GFC, during GFC, and post-GFC periods are 2003.2–2007.6, 2007.7–2009.5, and 2009.6–2018.12, respectively. All regressions include the log of previous equity investment and the other pull and push factors in the model 1.5, but the coefficients of those variables are omitted in the table to focus on the large investors' effect.

The result of Table 1.5 is consistent with that of Figure 1.5[17]. It implies that the two methods to find herding show a similar trend over the period. However, there is no evidence of herding based on the regression results while it still has evidence of herding according to the LSV measure since the value, around 7 – 8%, is still high compared to previous literature. It is inferred that the LSV measure is overestimated due to the inclusion of unintended herding.

[17]The average herding measure is relatively low during the global crisis period (2007.7 – 2009.5) while it is significantly high during pre and post-crisis.

Table 1.6: Large Investors' Effect by Investors' Size

	(1)	(2)	(3)	(4)	(5)	(6)
Large Investors' Effect (%)	0.243*	0.077	0.142**	0.050	0.262**	0.087**
	(0.123)	(0.096)	(0.054)	(0.083)	(0.105)	(0.041)
Small Investors' Effect (%)	-0.260	0.137	0.018	0.108	-0.099	-0.130
	(0.293)	(0.179)	(0.109)	(0.122)	(0.183)	(0.082)
Period	Pre GFC	Pre GFC	Pre GFC	Post GFC	Post GFC	Post GFC
Investor Size	>90th	75−90th	0−75th	>90th	75−90th	0−75th
Observations	9240	12960	61900	24772	35224	152351
R-squared	0.926	0.958	0.932	0.959	0.937	0.939
	(7)	(8)	(9)			
Large Investors' Effect[1](%)	0.072	0.131*	0.090**			
	(0.064)	(0.075)	(0.037)			
Small Investors' Effect[1](%)	-0.064	-0.086	-0.068			
	(0.117)	(0.187)	(0.064)			
Period	All	All	All			
Investor Size	>90th	75−90th	0−75th			
Observations	38292	54144	242251			
R-squared	0.945	0.939	0.933			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. The pre-GFC and post-GFC periods are 2003.2–2007.6 and 2009.6–2018.12, respectively. All regressions include the fixed effects, the log of previous equity investment, and the other pull and push factors in the model 1.5, but the coefficients of those variables are omitted in the table to focus on the large investors' effect. The rank of investor size is based on the size of equity investment among small investors, and I partitioned three groups of investor size (>90th, 75–90th, and 0–75th) based on the distribution of small investors' size.

Moreover, Table 1.6 shows that, in general, the large investors' effect is more significant as the size of investors gets smaller. Small investors whose size is below the 75th percentile have been significantly influenced by large investors throughout the period. The significance of the other groups depends on the period, yet overall, the effect of large managers on small ones who are above the 90th percentile is not valid while that on the 75–90th percentile small investors indicate a weak significance. The smaller size of investors induces a smaller information set and a less significant role in the market, leading them to rely on large investors more. This shows a similar trend to the LSV measure in Table 1.3[18] even though it might be overestimated.

Additional Finding

I examine not only large investors' effects but pull and push factors that are widely used in the analysis of capital flows in emerging markets. Overall, the notable result in Table 1.7 is that price factors - exchange rate and stock market index - significantly affect the equity fund investment of small investors. The equity fund investment of small investors increases with the higher return of equity - the growth rate of the exchange rate gets smaller or that of the stock market index is larger. And the effects of exchange rate and stock market index sustain for 1–2 months as shown in their lagged coefficients being still significant. It implies that investors take into account price factors as one of the critical priorities in determining equity investment.

Moreover, the growth rate of total reserve shows a positive correlation with the equity fund of small investors. Total reserve is one of the important measures for the solidness of EMEs, and hence a high level of total reserve induces non-resident investors to invest more. And the growth rate of US industrial production is another significant factor. As US industrial production declines, investors that are located in the US and other advanced countries prefer emerging markets to advanced countries, leading to an increase in equity

[18] Overall, the average LSV herding measure increases as the size of investors decreases.

investment in emerging markets.

It is shown that the effects of the other push and pull factors are insignificant, which is against the results of some literature. According to the previous studies, Koepke (2019) presents that portfolio equity tends to have a strong negative correlation with push factors - global risk aversion and mature economy interest rate - and some positive relationship with pull factors - domestic output growth and asset return. In the result of Table 1.7, however, there is no strong evidence of the negative effect of push factors. This is due to the large investors' effect that is not included in the previous literature. The equity fund investment of large investors already reflects the external conditions and hence small investors consider it as a proxy for global risk aversion without responding to external conditions additionally.

On the other hand, pull factors are observed to be significant. The difference in result between push and pull factors is due to the approach of analysis. This paper which is based on the investors' demand approach presents the importance of pull factors, particularly price factors, that are directly related to the return on the equity in the view of each individual investor. In contrast, most of the previous research is based on aggregate analysis, which shows that push factors have a more impact on the portfolio flows than pull factors in the context of the business cycle.

Table 1.7: Panel Regression Result - Pull/Push Factors

	(1)	(2)	(3)	(4)
Real Interest Rate	0.149	0.489	0.199	0.389
	(0.186)	(0.342)	(0.168)	(0.313)
Δ Industrial Production	-0.084	-0.055	-0.091	-0.071
	(0.057)	(0.055)	(0.057)	(0.057)
Δ Total Reserve	0.479***	0.393***	0.415**	0.336**
	(0.141)	(0.127)	(0.146)	(0.135)
Δ Exchange Rate	-0.789***	-0.788***	-0.805***	-0.802***
	(0.146)	(0.154)	(0.146)	(0.157)
Δ Stock Market Index	0.780***	0.775***	0.764***	0.758***
	(0.116)	(0.116)	(0.109)	(0.110)
US Real Interest Rate	-0.255	0.578	-0.184	0.503
	(0.301)	(1.168)	(0.341)	(1.180)
Δ US Industrial Production	-1.567**	-1.653**	-1.522**	-1.613**
	(0.601)	(0.603)	(0.611)	(0.609)
Δ US Stock Market Index	-0.188	-0.166	-0.206	-0.187
	(0.208)	(0.216)	(0.210)	(0.213)
Δ VIX	-0.041	-0.030	-0.042	-0.031
	(0.031)	(0.032)	(0.031)	(0.032)
Δ Exchange Rate$_{(t-1)}$		-0.327**		-0.373**
		(0.146)		(0.143)
Δ Exchange Rate$_{(t-2)}$		-0.280*		-0.331**
		(0.152)		(0.151)
Δ Stock Market Index$_{(t-1)}$		0.223*		0.234**
		(0.113)		(0.111)
Δ Stock Market Index$_{(t-2)}$		-0.048		-0.034
		(0.063)		(0.068)
Lagged Variables	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	334687	333187	334687	333187
R-squared	0.943	0.943	0.943	0.943

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. All regressions include the log of previous equity investment and the large and small investors' effect, but only the coefficients of pull and push factors are presented in the table. I include all the lagged variables of pull and push factors but only those of exchange rate and stock market index are presented because the other lagged variables turn out to be insignificant.

1.5.4 Application

Capital flows (or portfolio flows) show a distinctive aspect for extreme changes, such as surges and sudden drops, due to different economic conditions. Thus, the analysis of capital flows in exceptional cases is necessary to be differentiated from the ordinary case (Ghosh et al., 2014). In this regard, we can raise the following questions. Does the large investors' effect have a different impact on small investors depending on the equity investment changes of small investors? In which condition are small investors more affected by large investors' preceding actions?

I test the impact of large investors on small investors depending on whether the growth rate of each small investor's equity investment is extraordinary. Including the interaction term with a categorical variable that identifies the exceptional equity funds movement, the non-linear effect of large investors is observed. To check if the case is abnormal, I establish the categorical variable which is zero if the absolute value of equity growth rate is within the threshold of $\nu = 10$ or 20%, and one otherwise.

From the panel regression equation 1.5, the modified specification is as follows.

$$
\begin{aligned}
y_{ic,t} = &\beta_{B,1}\Delta\log(\text{large}_{c,t-1}) \times \mathbb{I}(|\Delta y_{ic,t}| < \nu) + \beta_{B,2}\Delta\log(\text{large}_{c,t-1}) \times \mathbb{I}(|\Delta y_{ic,t}| \geq \nu) \\
&+ \boldsymbol{\beta}_{pull}\mathbf{pull}_{c,t} + \boldsymbol{\beta}_{push}\mathbf{push}_{t} + \xi_i + \xi_c + \xi_m + \epsilon_{ic,t}
\end{aligned} \tag{1.6}
$$

where $\mathbb{I}$ is the indicator function. In the sample, the proportion of extreme flows with 10 and 20% are approximately 25 and 10% of all the small investors' observations, respectively.

Table 1.8 shows that small investors tend to follow the observed large investors' behavior more significantly when they remarkably change their equity investment. Small investors raise the equity investments by 0.3 – 0.75% as large investors increase their investments by 1%, which is much larger than the overall large investors' effect, 0.1%. It means that small investors consider large investors' preceding equity investment for more aggressive decisions while they determine their equity investment by their own information set for the relatively small changes. Columns (1), (3), and (5) report that the estimated effects of large investors on small investors are significantly higher than when small investors' equity growth rates are higher than 10% or lower than -10% ($\nu = 10\%$). This is consistent with the result of columns (2), (4), and (6) which suppose more extreme changes in equity investment ($\nu = 20\%$). As the threshold of extreme changes increases ($\nu = 10 \rightarrow 20\%$), the estimated coefficients of the large investors' effect in extraordinary flows become larger by 0.2 – 0.35. It implies that higher extreme changes in equity flows are closely related to the small investors' tendency to follow large investors. As presented in all the columns, however, small investors do not tend to follow large investors' preceding action for small changes in equity investment.

Table 1.8: Large Investors' Effect with Extraordinary Flows

	(1)	(2)	(3)	(4)	(5)	(6)
Large Investors' Effect × Dummy Variable						
$\lvert$Equity Growth$\rvert < 10\%$	0.010		0.023		0.042*	
	(0.015)		(0.034)		(0.021)	
$\lvert$Equity Growth$\rvert \geq 10\%$	0.312***		0.431***		0.383**	
	(0.109)		(0.137)		(0.177)	
$\lvert$Equity Growth$\rvert < 20\%$		0.006		0.027		0.027
		(0.012)		(0.033)		(0.018)
$\lvert$Equity Growth$\rvert \geq 20\%$		0.540**		0.763***		0.690**
		(0.194)		(0.251)		(0.325)
Period	All	All	Pre GFC	Pre GFC	Post GFC	Post GFC
Observations	342118	342118	85800	85800	217318	217318
R-squared	0.943	0.943	0.942	0.942	0.949	0.949

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. The pre-GFC and post-GFC periods are 2003.2–2007.6 and 2009.6–2018.12, respectively. All regressions include all the variables in the modified model 1.6, but the coefficients of those variables except for the interact term are omitted in the table to focus on the large investors' effect in extraordinary cases.

This result gives us an important policy implication. Under the circumstances that small investors show herding by following large investors, the equity flows become highly volatile, which might lead to destabilization in the emerging markets. For the emerging countries' governments, therefore, it is important to monitor if investors show herd behavior and to watch the large investment institutions' investment movements.

1.6 Conclusion

This chapter finds evidence of herding among small investors in emerging markets by using both the LSV method and the panel regression method. Although the LSV measure indicates the presence of herding among small investors in the dataset, there are some bias issues, such as the inclusion of unintentional herding that occurs when investors face similar economic conditions. To measure the level of herding accurately, I use a panel regression model with the control of macroeconomic variables. And I introduce the preceding equity investments of large investors as the key variable to find evidence of herding. As a result, herding is observed among small investors, and this tendency is obviously shown when small investors change their equity investments drastically.

This chapter contributes to the literature on herding in several respects. First, it sheds light on the herding of non-resident investors in emerging markets which has not been considerably studied. Second, it proposes a more robust and convincing method to find evidence of herding by controlling common factors which might lead to unintentional herding. It overcomes some problems that the LSV method which is extensively used in many empirical literature. Lastly, this research provides a new perspective on the analysis of capital or portfolio flows. Unlike the previous literature that focuses on trends in aggregated flows, I apply the demand approach to analyze the investors' behavior and find evidence of herding. It also helps understand the difference in the impacts of pull and push factors between individual investors' flows and aggregate flows.

Although this chapter proposes evidence of herding among small investors in emerging equity markets, we need to study further the reasons for herding. Why do small investors follow large investors? More research needs to be conducted to understand the interaction between large and small investors in emerging markets. By including specific data such as equity trade data or each investor's financial report, we can find the reasons for herding.

Chapter 2

THE EFFECT OF MACROPRUDENTIAL POLICY ON PORTFOLIO FLOW IN EMERGING MARKETS

2.1 Introduction

Macroprudential policies have been highlighted to increase the resilience of the financial system and mitigate financial risk since the global financial crisis in 2008. Particularly in emerging countries, which are vulnerable to fluctuations in cross-border capital flows since the financial crisis, emphasis has been placed on the appropriate and timely implementation of macroprudential policies to mitigate capital flow volatility and financial risks. In other words, macroprudential policies have played an important role as a buffer against macroeconomic shocks in emerging markets.

Research on the effectiveness of macroprudential policies has grown as the number of cases has increased after the global financial crisis (GFC). While most studies have focused on the policy effect on GDP or credit growth, some literature shows that macroprudential policies decrease the negative impact of capital flows on GDP growth (Neanidis, 2019; Bergant et al., 2020; Frost et al., 2020). And Eller et al. (2021) present that tighter macroprudential policies lower gross capital inflow volume and volatility. In addition, most of the empirical works evaluating the effects of macroprudential policies have been conducted in many countries, including advanced and emerging countries, but some studies show that the policy effects are greater in emerging countries (Cerutti et al., 2017; Richter et al., 2019).

However, there has been little research on how macroprudential policies affect individual institutional investors due to the lack of data. Considering the fact that some large institutional investors often destabilize emerging financial markets, it is meaningful for policymakers to analyze how macroprudential policies affect individual investors. I use the

EPFR (Emerging Portfolio Fund Research) Global dataset, which provides investor-level equity flow movements, to analyze individual investors' responses to macroprudential policies. Moreover, it provides high-frequency flow data, which enables analyze the prompt reaction of investors to policies.

One issue when analyzing the macroprudential policy effect is the reverse causality (or endogeneity) problem. In the analysis of policy effects on aggregate capital flows, there exists a correlation between aggregate flows and the activation of macroprudential policies, generating a bias. This is because policymakers consider the movement of aggregate flows when deciding whether to activate macroprudential policies, and flows are affected by policies. Many empirical studies on the macroprudential policy effect also indicate this caveat (Forbes, 2021; Bergant et al., 2020; Frost et al., 2020; Neanidis, 2019; Forbes et al., 2015). The investor-level analysis using the EPFR Global dataset contributes to mitigating the reverse causality problem since the correlation between equity flows of individual investors and macroprudential policies is insignificant.

Another issue that previous literature raises is omitted variable bias (Forbes, 2021). This is because the effect of macroprudential policy depends on various factors, including not only domestic characteristics but also external conditions. Furthermore, macroprudential policy is often used together with other policies such as monetary policy, making it difficult to evaluate the net policy effect. To address this issue, I apply the double machine learning method that Chernozhukov et al. (2018) introduce to estimate the policy effect of macroprudential policies on each investor. Double machine learning helps to analyze the causal effect in an accurate and robust way by effectively controlling the other confounding factors. The other factors are fitted by using machine learning methods such as random forest and neural networks.

One of the advantages of double machine learning is that it can include as many potential variables as possible and insignificant variables are canceled out in the estimation. I include not only pull factors that describe the domestic conditions, i.e. interest rate, and industrial production but also push factors that present external conditions, i.e. VIX, and U.S. interest rate. In addition, I also include lags of macro variables and fixed effects that control the unobserved characteristics of each investor, country, and time period. It can help to reduce the omitted variable bias when analyzing the policy effects.

As a result, I find evidence that macroprudential policies contribute to the stabilization of the fluctuation of equity flows in emerging markets. As the macroprudential policy tightens, the magnitude of change in equity flows dampens by 0.4 – 0.7 %, and the policy effect was found to be valid this month and the next month. Divided into before and after the GFC, the effect of macroprudential policies is negatively significant for the volatility of equity flows only after the GFC, but had no effect before the GFC. This is in line with the trend of macroprudential policies, which is that they play an important role in the market after the GFC based on the general consensus that the financial system needed to be regulated.

Disaggregating macroprudential regulations by the type as Alam et al. (2019) classify, only supply-loans regulation helps mitigate volatility in equity flows by 1 – 1.6 % after the GFC in emerging markets, which is stronger than the overall effect, 0.4 – 0.7 %. However, the demand-side and supply-non-loans regulations are shown not to be effective. This is due to the fact that investors consider the supply-side regulations, which are related to the soundness or the degree of development of the financial system in the market, rather than the demand-side tools when making equity investment decisions. Moreover, only the supply-loans tools are effective among supply-side regulations since they are less frequently used. Other supply tools that are frequently implemented are not effective because rational investors expect them to be often activated and have a low marginal effect.

And I find that the smoothing effect of macroprudential policies on the fluctuation of equity flows is due to the dampening of the volatility particularly on extreme flows. I split the two groups – high volatile (both 30% tails of the equity flow distribution) and non-high volatile groups, and obtain the result that the effect of tightening macroprudential policies is valid only in extreme flows. They reduce the fluctuation of equity flows by 1.2 – 2 % for extreme flows, which is much larger than the overall effect. However, the policy effect is close to zero for non-extreme flows. This implies that macroprudential policies contribute to stabilizing equity flow fluctuation by mitigating highly volatile flows in emerging markets.

Finally, I observe that the effect of macroprudential policies depends on the frequency of policy implementation in emerging markets. Tightening macroprudential policies do not affect investor decisions about equity flows in countries that have used policies more frequently, such as China, India, and South Korea. On the contrary, the policy effect on equity flow fluctuation is negatively significant in less frequently used countries, such as Chile, Colombia, and Thailand. The volatility of the flows in these emerging countries is shrunk by 1.2 – 1.4 %, which is much stronger than the overall effect. This is because the marginal effect of macroprudential policies is low in more experienced countries where many instruments have been already established. These results are also consistent with the policy-ineffectiveness proposition that rational investors tend to respond only to unexpected shocks (policies that are infrequently implemented) rather than expected shocks (policies that are frequently used).

This chapter contributes to analyzing the effect of macroprudential policies by using a double machine learning method with investor-level data. This method helps mitigate two issues, the reverse causality problem and omitted variable bias, raised in previous literature on the policy effect on capital flow, drawing consistent and robust conclusions. Also, it provides a new perspective on the policy effect by analyzing the investor-level dataset. The macroprudential policies help to mitigate the volatility of individual investors' flows, particularly extreme flows, and hence increase the resilience of the financial system in emerging countries.

The rest of the chapter proceeds as follows. Section 2.2 describes the dataset and provides relevant statistics about macroprudential policy. Section 2.3 introduces double machine learning and its advantage. Section 2.4 shows the overall effect of macroprudential policies on the fluctuation of equity flows and the effect by period and type. Section 2.5 presents the policy effect in extreme flows and in different frequencies of policy implementation and provides an implication. Section 2.6 concludes.

2.2 Data

2.2.1 Data Description

The macroprudential policy data is obtained from the integrated Macroprudential Policy (iMaPP) database provided by IMF[1]. Alam et al. (2019) construct the iMaPP database and finds evidence of macroprudential policy effects on household credit and house prices, not affecting private consumption and GDP growth by using the database. The iMaPP database provides monthly dummy-type indicators of tightening and loosening actions of various macroprudential policy instruments and a description of each policy action. The dataset provides the monthly change of macroprudential policy by country in view of 17 instruments such as the capital requirement for banks, limits on the net or gross open foreign exchange positions, and limits on loan-to-value ratios[2].

I collect the tightening change of macroprudential policy for 20 countries[3] from 2003.1 to 2018.12. And I generate a new dummy variable to indicate whether the tightening macroprudential policy is implemented. The new dummy variable is set as one if any policies of 17 instruments are activated, and zero otherwise. This differs slightly from the iMaPP database in that the new dummy variable represents one if any tool is activated, regardless of the number of activation policies provided by the original data. In order to apply the double machine learning method that only allows a binary dummy variable for treatment effect analysis, I modify the number of activated instruments as a binary variable. In addition, only a tightening action of macroprudential policy except for a loosening action is considered for the analysis. This is because the number of loosening cases is too small to obtain a consistent and robust outcome.

To collect the equity flows of each investor, I use the Emerging Portfolio Fund Research

[1] https://www.elibrary-areaer.imf.org/Macroprudential/Pages/iMaPPDatabase.aspx

[2] The detailed 17 instruments are introduced in Appendix F.

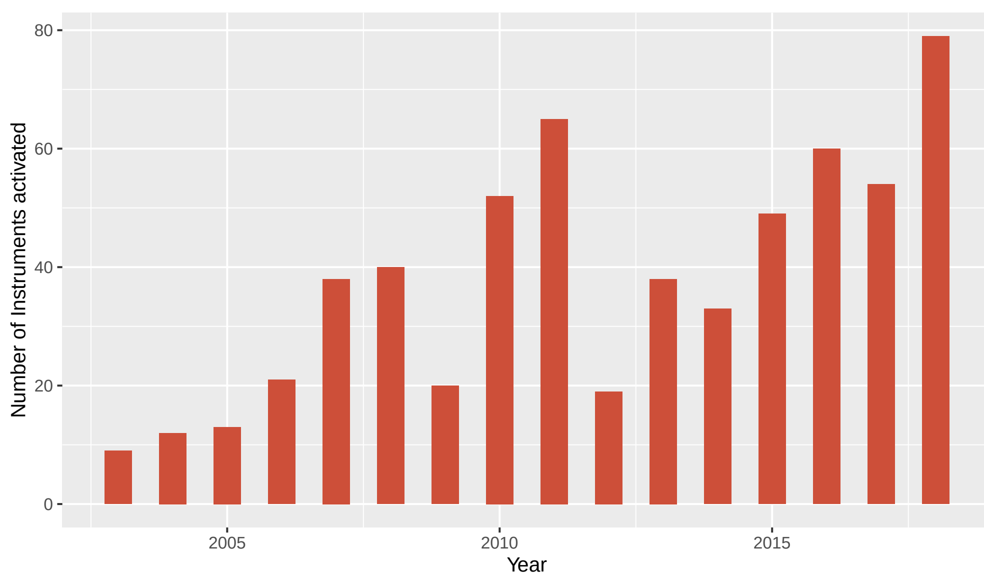
[3] Brazil, Chile, China, Colombia, Czech Republic, Hungary, Indonesia, India, Israel, South Korea, Mexico, Malaysia, Peru, Philippines, Poland, Russia, Thailand, Turkey, Taiwan, South Africa

(EPFR) Global dataset as used in Chapter 1. And the data source of other macro variables is explained in Appendix E.

2.2.2 Data Statistics

The number of tightening macroprudential policies has generally grown over the period as seen in Figure 2.1. Particularly, it shows a rise after the global financial crisis, and over 50 tightening macroprudential policies, recently about 80, are used in a year among 20 emerging countries. It is mainly due to the Basel III regulation that was developed after the global financial crisis and that strengthens bank capital requirements.

Figure 2.1: The Trend of the Number of Macroprudential Policies in EMEs



Notes: The instruments are counted only for the tightening macroprudential policy except for the loosening case. Also, only the tightening macroprudential policies for 20 emerging countries are considered in this graph.

Table 2.1 presents the total number of macroprudential policies varies much across emerging countries, depending on the economic situation of each country. In general, emerging countries with large economies, such as Brazil, China, India, South Korea, and Russia, implement more tightening macroprudential policies. However, the number of macroprudential policy instruments is relatively low in some countries, such as Chile, Colombia, the Czech Republic, and South Africa. Moreover, tightening macroprudential policies have generally intensified during and after the global financial crisis.

Table 2.1: The Trend of Macroprudential Policies by Country

	BRA	CHL	CHN	COL	CZE	HUN	IDN	IND	ISR	KOR
Number of Instruments	32	2	91	12	16	29	26	52	30	46
Average of Instruments	0.17	0.01	0.47	0.06	0.08	0.15	0.14	0.27	0.16	0.24
Pre GFC	0.02	0.00	0.30	0.04	0.00	0.02	0.02	0.26	0.00	0.23
GFC	0.17	0.00	0.67	0.33	0.00	0.00	0.04	0.29	0.04	0.08
Post GFC	0.23	0.02	0.51	0.02	0.14	0.24	0.21	0.27	0.25	0.28
	MEX	MYS	PER	PHL	POL	RUS	THA	TUR	TWN	ZAF
Number of Instruments	25	27	33	17	28	50	18	40	16	12
Average of Instruments	0.13	0.14	0.17	0.09	0.15	0.26	0.09	0.21	0.08	0.06
Pre GFC	0.02	0.02	0.08	0.09	0.06	0.04	0.08	0.04	0.02	0.00
GFC	0.04	0.00	0.26	0.04	0.17	0.29	0.04	0.25	0.13	0.00
Post GFC	0.20	0.23	0.20	0.10	0.18	0.36	0.11	0.28	0.10	0.10

Notes: 1. The instruments are counted only for the tightening macroprudential policy except for the loosening case.
2. Average of Instruments = Number of Instruments / Number of Months
3. The pre-GFC, GFC, and post-GFC periods are 2003.2–2007.6, 2007.7–2009.5, and 2009.6–2018.12, respectively.

In addition, macroprudential policies can be categorized by the characteristics of policies. Alam et al. (2019) classify 17 instruments of macroprudential policies into 4 groups – demand-side tools, supply-loans tools, supply-general tools, and supply-capital tools. First, demand and supply tools are distinct in whether the tool targets borrowers or financial institutions. And then, supply tools are classified by the characteristics of the target. In general, as shown in Table 2.2, supply-general and supply-capital tools have been the most used after the global financial crisis. It implies that emerging countries have focused on building and strengthening buffers of financial institutions to increase the resilience of the financial system. The relative frequency of implementation by the policy type differs by country because it depends on the economic conditions and the degree of financial system development in each country.

Table 2.2: The Trend of Macroprudential Policies by Type (Post GFC)

	BRA	CHL	CHN	COL	CZE	HUN	IDN	IND	ISR	KOR
Number of Instruments	27	2	59	2	16	28	24	31	29	32
Demand	1	1	7	0	5	7	2	2	2	8
Supply-loans	0	1	10	0	2	3	4	3	7	7
Supply-general	10	0	21	2	4	12	10	11	3	7
Supply-capital	8	0	11	0	3	3	4	11	11	6
Others	8	0	10	0	2	3	4	4	6	4
	MEX	MYS	PER	PHL	POL	RUS	THA	TUR	TWN	ZAF
Number of Instruments	23	26	23	11	21	41	13	32	12	12
Demand	0	3	0	1	7	0	3	2	3	0
Supply-loans	5	5	0	1	3	5	0	11	3	1
Supply-general	8	7	19	3	4	12	4	13	3	4
Supply-capital	6	5	2	3	5	20	6	6	3	6
Others	4	6	2	3	2	4	0	0	0	1

Notes: 1. The instruments are counted only for the tightening macroprudential policy except for the loosening case.
2. The demand tools include LTV and DSTI (limits on the debt-service-to-income ratio).
3. The supply-loans tools include limits on credit growth, loan loss provisions, loan restrictions, limits on the loan-to-deposit ratio, and limits on foreign currency loans.
4. The supply-general tools include reserve requirements, liquidity requirements, and limits on FX positions.
5. The supply-capital tools include leverage, countercyclical buffers, conservation buffers, and capital requirements.
6. Other instruments include tax, SIFI (systemically important financial institutions), and measures not captured in the above categories, e.g. stress testing, restrictions on profit distribution, and structural measures.
7. The time period is from 2009.6 to 2018.12.

2.2.3 The Importance of Investor-level Dataset

One of the problems previous research indicates in the analysis of policy effect is reverse causality (or endogeneity) problem (Forbes, 2021; Frost et al., 2020; Neanidis, 2019; Forbes et al., 2015). Aggregate (capital) flows have a correlation with the implementation of macroprudential policies. In other words, policymakers consider the movement of aggregate flows to determine whether to tighten macroprudential regulations while the flows are affected by the activation of the policies. This endogeneity generates a bias, without a guarantee of consistent outcome. Therefore, it is important to remove this endogeneity between the dependent variable and the treatment effect to obtain robust results. As a solution to this problem, some literature proposes the propensity score matching (PSM) approach[4] (Frost et al., 2020; Alam et al., 2019; Forbes et al., 2015).

In this paper, I analyzed the policy effect not on aggregate-level flows but on individual investor-level flows by using the EPFR Global dataset. This analysis contributes to mitigating the reverse causality problem[5] since the correlation between investors' equity flows and the activation of macroprudential policies is insignificant. In other words, policymakers tend to consider the aggregate flows rather than each individual investor's flow when deciding whether to implement macroprudential policies. Therefore, the investor-level analysis is important in this paper as a solution to the reverse causality problem.

[4]In order to eliminate the interaction effect between capital flows and the macroprudential policy variables, two-stage estimation is used. In the first stage, it estimates the probability of whether to conduct macroprudential policies at the current period, t, by regressing on the macroeconomic variables of the previous period, $t-1$. And then, in the second stage, it divides into a treatment group and a control group depending on whether macroprudential policies are activated and regresses the capital flows at the subsequent period, $t+1$, on policy action at the current period, t, for each group. Finally, the average treatment effect (ATE) is acquired by calculating the mean difference of interest between the two groups.

[5]In Appendix H, the effects of macroprudential policies on aggregate equity flows are not significant, which is against the fact that the policy effects on the flows of individual investors are significantly negative as shown in the next Section 2.4. It is due to the presence of causality between aggregate flows and macroprudential policies.

2.3 Model

2.3.1 Double Machine Learning

Machine learning (ML) methods show a great performance to fit the dataset but it has a pitfall with low interpretability. The black box includes complex combinations of computations that provide outstanding prediction but makes it difficult to understand the process inside the box, i.e. how each predictor affects the outcome. This is because high interpretability is closely related to the linearity of the model, which is far from the complex black box. In order to overcome the trade-off between precision (or performance) and interpretability, the semi-parametric model with the combination of a linear term and a machine learning part can be proposed. Chernozhukov et al. (2018) introduce double or debiased ML (DML) that not only estimates the treatment effect of a specific control among nuisance confounders but also uses machine learning methods such as random forests, neural nets, lasso, ridge, and various hybrids to maximize precision. DML is particularly useful for causal inference.

Chernozhukov et al. (2018) revisit the partially linear regression (PLR) model as follows.

$$Y = D\theta_0 + g_0(X) + U, \qquad E[U|X, D] = 0 \tag{2.1}$$

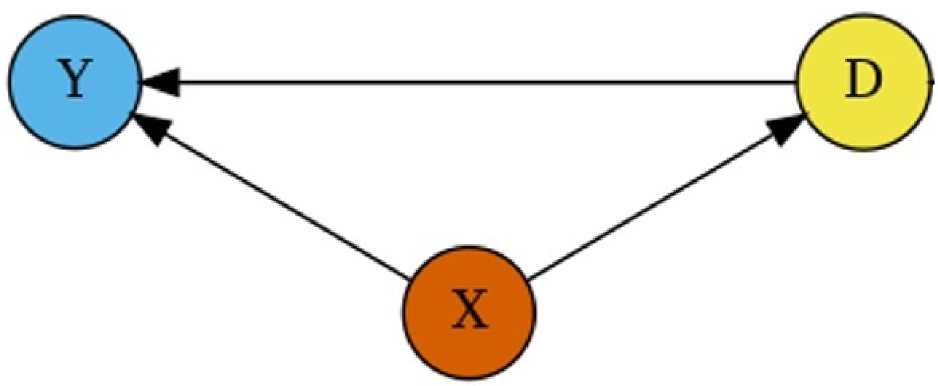
$$D = m_0(X) + V, \qquad E[V|X] = 0 \tag{2.2}$$

where Y is the outcome variable, D is the policy variable or treatment of interest, and high-dimensional vector X consists of other confounding covariates. U and V are stochastic error.

The first equation is the main regression. This regression consists of linear term and non-linear term which is implemented by machine learning methods, g_0. The policy effect or treatment effect can be estimated in the linear part while other covariates are controlled by a non-linear function. This combination contributes not only to the improvement of the interpretability of the interest variable through the linear term but also to the enhancement of the performance by using ML methods.

The second equation removes the bias from the endogeneity of the variable of interest, D, under the assumption that the policy variable or the treatment variable depends on other control variables. As in Figure 2.2, control variables, X, have an impact not only on the outcome, Y, but also on the treatment variable, D, and hence it is essential to remove the bias arising from this causality. The function, m_0, that explains the causality is implemented by ML methods.

Figure 2.2: Causal Diagram for PLR



In this chapter, the outcome variable, Y, is the absolute value of the equity flow's growth rate which presents the degree of fluctuation of the equity flows. And I set one as D if the macroprudential policy is conducted or zero otherwise. That is, the treatment is whether the macroprudential policy is implemented. θ_0 is the main coefficient of interest, which shows how the macroprudential policy affects the volatility of equity flows. X is the macro variable set that affects both equity flows and the implementation of the macroprudential policy – the real interest rate, the growth rate of industrial production, the growth rate of the total reserve, the growth rate of the exchange rate, the growth rate of the stock market index, the growth rate of VIX, U.S. real interest rate of U.S., the growth rate of U.S. industrial production, the growth rate of U.S. stock market index (Dow Jones Industrial Average). And the first, second, and third lagged variables of each macro variable are included in X, too[6]. Moreover, X also contains dummy variables for each investor, each country, and each month to consider the fixed effect[7].

And I test 4 models as functions, g_0 and m_0 – simple linear model, random forests, neural networks, and boosted tree[8]. Random forests, neural networks, and boosted tree are widely used in machine learning because they provide outperformed predictions for high-dimensioned data.

2.3.2 The advantage of DML with respect to the caveat of previous studies

One issue the previous literature raises is omitted variable bias (Forbes, 2021). The effect of macroprudential policy depends on various factors, including not only domestic characteristics but also external conditions. Also, macroprudential policy is often used together with other policies such as monetary policy, making it difficult to evaluate the net policy effect. However, it is so demanding to involve all the factors including latent variables related to macroprudential policies when setting up the regression model, resulting in omitted variable bias. Moreover, serious bias can occur due to the correlations between variables even if we include all the possible factors in the model.

Double machine learning has the advantage of processing high-dimensional data. It can include as many potential variables as possible and insignificant variables are canceled out in the estimation. I involve not only all the related macro variables such as pull and push factors[9] but also the lags of these variables in the model. In addition, I include the fixed effects

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[6] I use 9 macro variables and generate 3 lag variables for each macro variable, and thus the total 36 covariates are included in X.

[7] There are 208 investors, 20 countries, and 12 months in the dataset, respectively. Hence, I generate 207 dummies for investors, 19 dummies for the country, and 11 dummies for the month to control the unobserved characteristics.

[8] I explain each machine learning method and its implementation in Appendix G.

[9] The pull factors describe the domestic economic conditions such as interest rate, industrial production, and the stock index, while the push factors represent the external conditions such as the U.S. interest rate,

to reflect the unobserved characteristics of each investor, country, and month. This method helps to reduce the omitted variable bias when analyzing the effects of macroprudential policies.

2.4 Results

2.4.1 Overall Policy Effect

Table 2.3: The Overall Effect of Macroprudential Policies

Outcome	Linear	PLR model			
		(1)	(2)	(3)	(4)
Y_t	-0.1212	-0.4070*	-0.4420*	-0.5661**	-0.5075
	(0.2016)	(0.2041)	(0.2014)	(0.1958)	(0.2677)
Y_{t+1}	-0.3700	-0.3769	-0.6483**	-0.6820***	-0.7293**
	(0.2011)	(0.2066)	(0.2050)	(0.1967)	(0.2733)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors (HC2) in parentheses.
Notes: 1. Linear model in the second column is the simple linear regression model as follows:

$$Y_{ic,t+h} = D_{c,t}\theta_0 + \boldsymbol{\beta X} + \xi_i + \xi_c + \xi_m + \epsilon_{ict}$$

where $Y_{ic,t+h}$ is the absolute value of the investor i's equity flow's growth rate in the country c at time $t+h$ where $h \in \{0,1\}$, $D_{c,t}$ is the treatments of tightening macroprudential policies in the country c at time t. θ_0 is the treatment effects of interests, correspondingly. X includes all the push and pull factors, and ξ_i, ξ_c, and ξ_m represent the latent variables for investors, countries, and months, respectively.
2. The dependent variable, Y_{t+h}, in the first column of the table is the absolute value of the investor's equity flow's growth rate at time $t+h$ where $h \in \{0,1\}$, meaning the degree of fluctuation of the investor's equity flow.
3. In the PLR model, g_0 and m_0 are specified as follows:
(1) Linear regression model, (2) Random forest, (3) Neural networks, (4) Boosted tree
4. The time period is from 2003.2 to 2018.12 in each regression.

Table 2.3 exhibits the overall treatment effect of macroprudential policies. In general, the tightening macroprudential policies have a negative impact on the fluctuation of investors' equity flows this and next month. The magnitude of change in equity flows decreases by 0.4 – 0.7 % as macroprudential policies are tightened. This result supports the effectiveness of

the U.S. industrial production, and VIX.

macroprudential policies since it contributes to reducing the volatility of investors' equity flows. Moreover, it shows that the policy effect becomes stronger and more significant in the next month. The degree of contraction of equity flows fluctuation enlarged from 0.4 – 0.56 % to 0.64 – 0.73 % in the next month.

Also, we can find that the effects of macroprudential policies are not significant in the simple linear regression model as shown in the second column of Table 2.3. It implies that the linear model underestimates the effect of macroprudential policies. Moreover, the policy effect appears weak or insignificant when using a linear model as the function of the PLR model rather than other machine learning methods. This is because the linear regression model does not fit many covariates well, leading to a bias in the treatment effect.

2.4.2 Policy Effect by Period: Prior GFC vs. Post GFC

Now, I split the period before and after the global financial crisis (GFC) since the crisis was an important trigger to highlight the role of macroprudential policy. Under the general consensus that the financial system including financial institutions needed to be regulated, policymakers in each government have increased the number and kind of macroprudential policies after the GFC. Hence, the effect of macroprudential policies can be changed before and after the GFC.

Table 2.4 shows the effect of macroprudential policies before and after the GFC. All the coefficients in Panel A are not significant, implying that macroprudential policies did not affect investor decisions on equity flows before the crisis. After the GFC, however, the effect of macroprudential policies on investors has changed as shown in Panel B. It shows evidence that, after the crisis, macroprudential policies have negatively affected the fluctuation of investors' equity flows, particularly in the next month. The fluctuation of investors' equity flows in the next month of macroprudential policies being activated has shrunk by 0.5 – 1 % after the GFC. It means that macroprudential policies have contributed to stabilizing the equity flow movements of individual investors, which is in line with the purpose of the policy. This is because investors regard the activation of macroprudential policies as a reduction of

Table 2.4: The Effect of Macroprudential Policies by Period

	A. Prior-GFC (2003.2 – 2009.5)			
Outcome	PLR model			
	(1)	(2)	(3)	(4)
Y_t	0.3409	0.5712	0.5235	0.2933
	(0.4512)	(0.4649)	(0.4317)	(0.8426)
Y_{t+1}	0.6626	0.5147	0.4397	-0.1523
	(0.4623)	(0.4734)	(0.4370)	(0.8695)
	B. Post-GFC (2009.6 – 2018.12)			
Outcome	PLR model			
	(1)	(2)	(3)	(4)
Y_t	-0.0543	-0.2684	-0.3065	-0.4245
	(0.2338)	(0.2296)	(0.2159)	(0.3325)
Y_{t+1}	-0.4034	-0.6177**	-0.4940*	-1.0000**
	(0.2371)	(0.2335)	(0.2206)	(0.3330)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors (HC2) in parentheses.
Notes: 1. The dependent variable, Y_{t+h}, in the first column of the table is the absolute value of the investor's equity flow's growth rate at time $t + h$ where $h \in \{0, 1\}$, meaning the degree of fluctuation of the investor's equity flow.
2. In the PLR model, g_0 and m_0 are specified as follows:
(1) Linear regression model, (2) Random forest, (3) Neural networks, (4) Boosted tree

uncertainty in the markets due to an improvement in financial system soundness.

I will focus on the effect of macroprudential policies after the GFC in the following sections because the role of macroprudential policies has been reestablished after the GFC and because the purpose of this chapter is to analyze the smoothing effect of macroprudential policies.

2.4.3 Policy Effect by Type of Policy: Demand Side vs. Supply Side

The effect of macroprudential policy can be analyzed by the type of policy Alam et al. (2019) introduce. I categorize macroprudential policy into 3 types – demand side, supply-loans, and supply-non-loans policy. The demand-side tools, such as LTV (Loan-to-Value ratio) and DSTI (Debt-Service-to-Income Ratio), target borrowers while other supply-side tools are aimed at financial institutions. Supply-loans tools are supply-side policies that affect the loan, such as limits on credit growth, loan loss provision, and loan restrictions. Supply-non-loans tools are supply-side methods that are not categorized as supply-loan tools, such as reserve requirements, liquidity requirements, and capital requirements. These consist of supply-general tools and supply-capital tools as Alam et al. (2019) classify. I integrate two types of instruments since they have no difference in that the effects of both types are insignificant.

It is presented that only the effects of supply-loan tools are negatively significant after the GFC while the other two types of policies are not effective as shown in Table 2.5. Supply-loans tools in Panel B dampen the fluctuation of investors' equity flows by 1 – 1.6 %, which is stronger than the overall effect in Table 2.3. However, the policy effects of demand-side measures and supply-non-loans measures are found to be positive or insignificant, as shown in Panels A and C.

It means that macroprudential policies targeting financial institutions, particularly the direct regulation of lending, have an impact on non-resident investors' decisions on equity flows, while the instruments aimed at borrowers or at financial institutions not related to lending do not affect investors. First, this is due to the characteristics of tools. Investors

Table 2.5: The Effect of Macroprudential Policies by Policy Type (Post-GFC)

A. Demand Side Policies				
Outcome	PLR model			
	(1)	(2)	(3)	(4)
Y_t	0.6111	0.0790	-0.0602	1.4670
	(0.5611)	(0.6020)	(0.5668)	(1.0050)
Y_{t+1}	0.8818	1.3080*	1.9729***	1.1140
	(0.5932)	(0.6310)	(0.5826)	(1.0930)
B. Supply-loans Policies				
Outcome	PLR model			
	(1)	(2)	(3)	(4)
Y_t	-1.1490*	-1.6763***	-1.3021**	-0.9995
	(0.4640)	(0.4739)	(0.4518)	(1.2155)
Y_{t+1}	-0.3193	-0.9956*	-1.2644**	-0.2954
	(0.4757)	(0.4909)	(0.4559)	(1.1466)
C. Supply-non-loans Policies				
Outcome	PLR model			
	(1)	(2)	(3)	(4)
Y_t	0.0067	0.4395	0.4243	-0.0740
	(0.3028)	(0.2967)	(0.2710)	(0.5932)
Y_{t+1}	-0.4769	-0.5137	-0.5017	-0.5093
	(0.3060)	(0.2963)	(0.2700)	(0.5874)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors (HC2) in parentheses.
Notes: 1. In the PLR model, g_0 and m_0 are specified as follows:
(1) Linear regression model, (2) Random forest, (3) Neural networks, (4) Boosted tree
2. The demand side policies include LTV and DSTI (limits on the debt-service-to-income ratio). I drop Mexico and Peru in the regression since there is no observation for demand side tools in these two countries.
3. The supply-loans policies include limits on credit growth, loan loss provisions, loan restrictions, limits on the loan-to-deposit ratio, and limits on foreign currency loans. Brazil, Colombia, Peru, and Thailand are dropped in the regression since supply-loans tools are not used.
4. The supply-non-loans policies consist of supply-general policies and supply-capital policies. These policies include reserve requirements, liquidity requirements, limits on FX positions, leverage, countercyclical buffers, conservation buffers, and capital requirements. Chile is dropped in the regression since supply-non-loans tools are not used.
5. The time period is from 2009.6 to 2018.12 in each regression.

consider the soundness or the degree of development of the financial system in the market when deciding the equity investment, which is related to supply-side policies. Hence, the tightening of supply-side regulation that enhances the soundness of the financial systems helps to smooth the fluctuation of equity flows. In contrast, the volatility of equity investment can increase for the tightening of demand-side instruments because it might be regarded as the expansion of uncertainty in the market. Second, this result is related to the frequency of policy implementations. Supply-loans tools have been less frequently used compared to other types of supply tools as shown in Table 2.2. Investors tend to respond more to unexpected shocks such as less frequently used policies by rational expectation. Furthermore, the more times macroprudential policies are used, the smaller the marginal effect of the policies. Therefore, less frequently used supply-loans tools are more effective than other types of supply tools.

2.5 Application

2.5.1 Policy Effect by Volatility

We find evidence in the previous section that macroprudential policies play a role in smoothing the fluctuation of equity flows. To evaluate the policy effect meticulously, it is necessary to analyze the effect in case of extreme flows. This is because extreme flows severely increase financial risk in the market, and hence policymakers must implement macroprudential policies in a timely and proper manner, particularly focusing on extreme flows.

I define high volatility of the flows as both 30% tails of the equity flow distribution and then separate the two groups – high volatile group and non-high volatile group. Table 2.6 shows that macroprudential policies are effective only when the equity flows are highly volatile. The tightening policies reduce the high fluctuation of equity flows by 1.2 – 2 % in Panel A, which is much larger than the overall effect in Table 2.3. However, the policy effects are close to zero for non-high volatile flows as shown in Panel B, which means that macroprudential policies do not affect the equity flow fluctuation.

Table 2.6: The Effect of Macroprudential Policies by the Degree of Volatility (Post-GFC)

A. High Volatility (30% in both tails)				
Outcome	PLR model			
	(1)	(2)	(3)	(4)
Y_t	-0.1467	-1.6774***	-1.2791***	-0.8421*
	(0.3520)	(0.3477)	(0.3298)	(0.4182)
Y_{t+1}	-0.6283	-2.0596***	-1.9584***	-1.3884**
	(0.3594)	(0.3588)	(0.3374)	(0.5045)

B. Non-high Volatility				
Outcome	PLR Model			
	(1)	(2)	(3)	(4)
Y_t	0.0004	0.0061**	0.0061**	0.0043*
	(0.0019)	(0.0020)	(0.0019)	(0.0019)
Y_{t+1}	-0.0004	0.0085***	0.0087***	0.0033
	(0.0019)	(0.0020)	(0.0020)	(0.0021)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors (HC2) in parentheses.
Notes: 1. The dependent variable, Y_{t+h}, in the first column of the table is the absolute value of the investor's equity flow's growth rate at time $t + h$ where $h \in \{0, 1\}$, meaning the degree of fluctuation of the investor's equity flow.
2. In the PLR model, g_0 and m_0 are specified as follows:
(1) Linear regression model, (2) Random forest, (3) Neural networks, (4) Boosted tree
3. The time period is from 2009.6 to 2018.12 in each regression.

This result implies that tightening macroprudential policies contribute to stabilizing the equity flow fluctuation by particularly mitigating highly volatile flows in emerging markets. And this is consistent with the goal of macroprudential policies.

2.5.2 Policy Effect by Country

The effect of macroprudential policies differs by country since each country confronts different internal and external situations. The analysis of the policy effect by country provides a clue of the condition that macroprudential policies work better. Many emerging countries have generally implemented macroprudential policies after the GFC, but the frequency of the policy implementation varies from country to country as in Table 2.1. The frequency might be a key factor to determine the policy effect in emerging markets. In this section, I choose the five emerging countries that have implemented macroprudential policies most frequently (China, India, South Korea, Russia, and Turkey) and the seven countries that have conducted them the least (Chile, Colombia, Czech Republic, Philippines, South Africa, Taiwan, and Thailand). And then, I run the regression separately to analyze the policy effect in each subgroup.

Table 2.7 presents that macroprudential policies are effective only where they are less frequently used. In the five countries that have frequently implemented, the policy effects on investors' equity flows are insignificant as shown in Panel A. On the contrary, in Panel B, tightening macroprudential policies in less frequently used seven countries typically reduce the magnitude of equity flow volatility by 1.2 – 1.4 %. And this is stronger than in Table 2.3 which covers all 20 emerging countries. To summarize, macroprudential policies are proven to be more effective in countries that have less implemented them.

Why do macroprudential policies work better in less experienced countries? This is because of the different marginal effects of macroprudential policies in each country. In more experienced countries such as China and South Korea, many instruments of macroprudential policies have been already established, and hence, the marginal effect of additional macroprudential policies is very low. And investors do not respond to additional policies in those

Table 2.7: The Effect of Macroprudential Policies by Country (Post-GFC)

A. 5 Countries that have implemented most frequently				
Outcome	PLR model			
	(1)	(2)	(3)	(4)
Y_t	0.1226	0.1213	-0.1753	-1.0250
	(0.3374)	(0.3601)	(0.3277)	(1.0460)
Y_{t+1}	0.1813	-0.2079	-0.2907	0.5764
	(0.3440)	(0.3669)	(0.3313)	(1.1129)

B. 7 Countries that have implemented the least				
Outcome	PLR Model			
	(1)	(2)	(3)	(4)
Y_t	-1.0960	-1.4133*	-1.2192*	-3.6910
	(0.6300)	(0.6061)	(0.5434)	(2.7190)
Y_{t+1}	-1.2251*	-1.1054	-1.3685*	-5.2680**
	(0.6219)	(0.6175)	(0.5458)	(2.0200)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors (HC2) in parentheses.
Notes: 1. The dependent variable, Y_{t+h}, in the first column of the table is the absolute value of the investor's equity flow's growth rate at time $t + h$ where $h \in \{0, 1\}$, meaning the degree of fluctuation of the investor's equity flow.
2. In the PLR model, g_0 and m_0 are specified as follows:
(1) Linear regression model, (2) Random forest, (3) Neural networks, (4) Boosted tree
3. The time period is from 2009.6 to 2018.12 in each regression.
4. 5 countries in A are China, India, South Korea, Russia, and Turkey. And 7 countries in B are Chile, Colombia, Czech Republic, Philippines, South Africa, Taiwan, and Thailand.

countries due to the low effect. In contrast, the marginal effect of macroprudential policies is so high in less experienced countries such as Chile and Thailand that investors consider introducing additional macroprudential policies as a significant shock. Hence, macroprudential policies play an important role in stabilizing the fluctuation of investors' equity flows in those countries. It is consistent with the result of Neanidis (2019) that countries with relatively open and deep financial systems have low marginal gains from macroprudential policies. This is because open emerging countries with a well-equipped financial system have generally implemented macroprudential policies more often.

Furthermore, this result is in line with the policy-ineffectiveness proposition based on rational expectation theory. Investors with rational expectations do not tend to respond to expected shocks such as frequently used policies. However, unexpected shocks, such as policies that are infrequently implemented, can have a significant impact on investors, and they take them into account when making equity investment decisions. Therefore, macroprudential policies are more effective in less experienced emerging countries.

2.6 Conclusion

Macroprudential policies are often implemented in emerging markets to mitigate financial risk and improve the financial system, particularly after the GFC. Hence, it is important to analyze the effects of macroprudential policies and implement the policies in a timely and appropriate manner to maximize their effectiveness. By applying double machine learning with the investor-level dataset, which reduces the bias from reverse causality and omitted variables, I find that macroprudential policies dampen the volatility of equity flows after the GFC in emerging markets, particularly by curbing extreme flows. In addition, macroprudential policies are found to be more effective as the frequency of policy implementation is lower, which is due to the rational expectations of investors and the inverse relationship between the frequency of policy implementation and the marginal effect of macroprudential policies.

However, further research on the various channel of how macroprudential policies affect investors is still needed to be conducted. Also, it would be meaningful to compare the effects of macroprudential policies with those of other policies, such as capital controls or monetary policy.

Notwithstanding, this chapter contributes to the literature on macroprudential policy in several aspects. First, it introduces double machine learning as the tool for analyzing policy effects, which enables to use of high-dimensional data and improves performance. Also, it develops research on the impact of macroprudential policies on capital flows by using investor-level data and segmenting the effect by various aspects.

Chapter 3

THE SEQUENTIAL MODEL OF EQUITY INVESTMENT OF LARGE AND SMALL INVESTORS

3.1 Introduction

Stock markets are efficient in that stock price reflects all the information about the individual stock as well as the whole market. However, global equity markets, particularly emerging markets, are sometimes inefficient (Bartram and Grinblatt, 2021), leading to herd behavior which is often observed. In inefficient markets where all information is not available, investors determine their equity investment based not only on available information but also on others' investment decisions. Consequently, as in Chapter 1, small investors show herd behavior in equity investment by following large investors' behaviors.

There have been studies explaining behavioral or psychological feedback mechanisms in the stock market. Keynes (1936) and Shiller (2000) describe the role of expectation of others' behavior to explain speculative bubbles in stock markets. Graham and Dodd (1934) indicate that the short-term stock market is determined by voting, a majority-rule process, while the long-term market is rational. These studies support the empirical fact that investors consider others' behavior when deciding on equity investments. However, there has been little research about the model that this strategic complementarity in the stock market.

Under information asymmetry, small investors who have limited information can follow large ones who have a much larger set of information, while underreacting to their own information. Corsetti et al. (2004) introduce the sequential model that the small traders are affected by the presence of the large trader. The observed preceding trading position of the large trader is recognized as a significant signal and hence it has an impact on the trading decision of small traders. This heterogeneity of investors might result in herd behavior in equity markets.

To describe herd behavior in equity markets, I introduce the simple model in which small investors make decisions on equity investment in the presence of large investors. The model analyzes the impact of the large investor on small investors based on the beauty contest model introduced by Keynes (1936). The beauty contest model shows strategic complementarity, implying that the player takes into account not only the fundamentals but also other players' responses. As described in the beauty contest model in Morris and Shin (2002), investors receive private and public information on the fundamental value of the equity, and then decide on the equity investment considering both the fundamentals and other investors' decisions. Based on this scheme, I suppose two important assumptions to specify the model. First, as in the setting in Corsetti et al. (2004), I introduce a large investor whose decision affects the market aggregates and equilibria and a continuum of small investors with a measure of zero meaning negligible impact on the aggregates. Another assumption is that the large investor moves first and her information is disseminated to small investors. And then, small investors make their decisions after observing large investors' decisions and information.

In the model, the optimal strategy for small investors is represented by a linear combination of private information, public information, and the large investor's action. The optimal response to the private signal, public signal, and large investor's action depends on the beauty contest parameter. The more weight investors place on the other investors' actions (higher beauty contest parameter), the more sensitive they are to the behavior of the large investor, but less sensitive to private and public information. Particularly in emerging markets, the beauty contest parameter is high due to the limited available information, making small investors more dependent on the action of the large investor.

Also, I find evidence of herding among small investors under the presence of a large investor. As large investor dominates the market more, small investors follow the behavior of large investor more, leading to a higher level of herding among small investors. It means that the level of herding is associated with the degree of market concentration. In emerging markets, the market is usually dominated by a few large investors. It implies that small investors depend more on large investors, leading to herding. This result provides policy-makers an implication that they should watch the market concentration and monitor the dominant players to understand herd behavior in emerging markets.

3.2 Setting

There is a continuum of investors indexed by i in a unit interval $[0,1]$. There exists a single large investor indexed by $i=1$, which market share is $\lambda \in [0,1]$ that represents the market concentration. On the other hand, a number of small investors are homogeneous and indexed by j in $[0,1)$. Their aggregate market share is $1-\lambda$. The small investors' idiosyncratic information and behaviors disappear in the aggregate market due to diversification while that of the large investor does not.

Now, all investors determine their equity investment, which is the value of the stock holding[1]. As Keynes' beauty contest, investors consider not only the intrinsic value of the stock[2] but also others' expectations of equity investments. To make it simple, I assume an investor's action is the increase or decrease of equity investment compared to the previous period.

And I assume that the large investor makes a decision on equity investment first, and then small investors determine their investments given their own information and the large investor's decision. Let small investor j's action $s_j \in \mathbb{R}$ be the equity investment investor j determines. And, as in Morris and Shin (2002), the quadratic payoff function[3] for small investor j is defined as follows:

$$u_j(s_j; f, \bar{s}, l) \equiv -(1-\theta)(s_j - f)^2 - \theta\big[s_j - \lambda l - (1-\lambda)\bar{s}\big]^2 \tag{3.1}$$

[1] The value of the stock holding = Number of shares of the stock × Stock price

[2] The intrinsic value of the stock = Sum of expected discounted cash flow for the stock = $\sum_{k=t}^{\infty} \mathbb{E}_t\left[\frac{CF_k}{(1+r)^k}\right]$

[3] Many studies that describe a "beauty-contest" game suppose a quadratic pay-off (or loss) function in which the player's payoff is determined by the proximity of his action to both the underlying fundamentals and the average action of other players.(Hellwig and Veldkamp, 2009; Myatt and Wallace, 2012, 2014; Baeriswyl and Cornand, 2014; Cornand and Heinemann, 2014)

where θ is the "beauty contest parameter", which is a constant, with $0 < \theta < 1$.

The payoff function for the small investor j consists of two components. The first term, $(s_j - f)^2$, is a standard quadratic loss in the distance between the investor j's action s_j and the underlying fundamentals f. The fundamentals f indicate the change in the intrinsic value of the equity. Hence, the goal of each investor is to determine her equity investment s_j closely to the fundamentals f. f is randomly drawn from a normal distribution, $f \sim \mathcal{N}(0, \sigma_f^2)$, but it is not observable. The second term, $\left[s_j - \lambda l - (1-\lambda)\bar{s}\right]^2$, is the "beauty contest" term, where l is the observed large investor's action and $\bar{s}$ $(= \int_{[0,1)} s_j dj)$ is the average action of small investors. It represents the loss of investor j deviated from the expectation of equity investment of all investors, $\lambda l + (1-\lambda)\bar{s}$, implying the strategic behavior.

Small investor j maximizes her utility u_j, and her action s_j is determined by the first-order condition as follows:

$$s_j = (1-\theta)\mathbb{E}_j[f] + \theta\mathbb{E}_j\left[\lambda l + (1-\lambda)\bar{s}\right] \tag{3.2}$$

where the operator $\mathbb{E}_j[\cdot]$ is investor j's expectation.

The equation 3.2 shows that small investors consider not only their own information on the fundamentals but also their expectation of other investors' behaviors. And the weight of each term in the function depends on the beauty contest parameter θ. If $\theta = 0$, the investor determines her action without considering others' actions. In contrast, $\theta = 1$ means that the investor takes into account only others' behaviors ignoring her own signal, and acts strategically.

Now, investors choose their actions by an observable signal which includes noise. First, each small investor receives its own private signal x_j with noise $\epsilon_{x,j}$ as follows:

$$x_j = f + \epsilon_{x,j}, \tag{3.3}$$

where the noise is normally distributed, $\epsilon_{x,j} \sim \text{iid}\,\mathcal{N}(0, \sigma_x^2)$.

And the signal of the large investor is defined as

$$z = f + \epsilon_z, \tag{3.4}$$

where the noise is normally distributed, $\epsilon_z \sim \mathcal{N}(0, \sigma_z^2)$, and the variance of the noise is different from that of small investors' noise ($\sigma_z^2 \neq \sigma_x^2$). Moreover, f, $\epsilon_{x,j}$, and ϵ_z are mutually independent. As mentioned above, the information of the first mover, the large investor, is disseminated. Thus, small investors also take this signal into account in determining investment strategy, and the public signal z plays a critical role to the small investors.

Small investor $j \in [0, 1)$ predicts the fundamentals by using the private and public information (x_j and z, respectively) as follows:

$$\mathbb{E}_j[f] = \alpha_x x_j + \alpha_z z, \tag{3.5}$$

where $\alpha_x = \sigma_x^{-2}/(\sigma_f^{-2} + \sigma_x^{-2} + \sigma_z^{-2})$ and $\alpha_z = \sigma_z^{-2}/(\sigma_f^{-2} + \sigma_x^{-2} + \sigma_z^{-2})$. And the large investor's expectation is

$$\mathbb{E}_1[f] = \beta z, \tag{3.6}$$

where $\beta = \sigma_z^{-2}/(\sigma_f^{-2} + \sigma_z^{-2})$ which is larger than α_z.

3.3 *Strategy of Small Investors*[4]

The first-order condition in the equation 3.2 provides a linear equilibrium. It is rewritten as

$$s_j = (1-\theta)\mathbb{E}_j[f] + \theta\big[\lambda l + (1-\lambda)\mathbb{E}_j[\bar{s}]\big]. \tag{3.2.1}$$

The equation 3.2.1 describes that the optimal strategy s_j is the linear combination of expectations of fundamentals (f) and other investors' actions (l and $\bar{s}$).

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[4]The detailed derivations and proofs are in Appendix I.

Suppose there is no strategic behavior ($\theta = 0$). Then, the small investor's payoff depends only on the fundamentals regardless of others' actions. And the small investor's problem simplifies to a conventional problem which is a signal extraction from the noise. Thus, the optimal action becomes

$$\begin{aligned} s_j^{se} = \mathbb{E}_j[f] &= \alpha_x x_j + \alpha_z z \\ &\equiv \psi_x^{se} x_j + \psi_z^{se} z, \end{aligned} \tag{3.7}$$

The equilibrium with zero beauty contest is the small investor's expected belief in the fundamentals and is independent of the large investor's market share (λ).

In general, when $\theta \in [0, 1)$, the optimal strategy is a linear function of signals as presented in Morris and Shin (2002)[5].

$$s_j^* \equiv \psi_x x_j + \psi_z z + \psi_l l \quad \text{for } j \in [0, 1) \tag{3.8}$$

Then, investor j's belief in the average action of small investors is

$$\begin{aligned} \mathbb{E}_j[\bar{s}] &= \psi_x \mathbb{E}_j[x_j] + \psi_z z + \psi_l l = \psi_x \mathbb{E}_j[f] + \psi_z z + \psi_l l \\ &= \psi_x(\alpha_x x_j + \alpha_z z) + \psi_z z + \psi_l l. \end{aligned} \tag{3.9}$$

Plugging equations (3.5) and (3.9) into equation (3.2), we obtain

$$s_j^* = (1-\theta)[\alpha_x x_j + \alpha_z z] + \theta\big\{\lambda l + (1-\lambda)\big\{\psi_x(\alpha_x x_j + \alpha_z z) + \psi_z z + \psi_l l\big\}, \tag{3.10}$$

Solving the equations (3.8) and (3.10), we can derive the optimal responses to private signal,

[5]The equilibrium in (3.8) is the linear combination of not only private and public information(x_j and z, respectively) presented in Morris and Shin (2002) but also the large investor's action(l). Small investors observe both signals l and z, but the signal l is distinguished from the public signal z in that l is the posterior outcome based on the prior information z.

public signal, and large investor's action as follows.

$$\psi_x = \left[\frac{1-\theta}{1-\theta(1-\lambda)\alpha_x}\right]\alpha_x, \tag{3.11}$$

$$\psi_z = \left\{\frac{1-\theta}{[1-\theta(1-\lambda)][1-\theta(1-\lambda)\alpha_x]}\right\}\alpha_z, \tag{3.12}$$

$$\psi_l = \frac{\lambda\theta}{1-\theta(1-\lambda)} = 1 - \frac{1-\theta}{1-\theta(1-\lambda)}. \tag{3.13}$$

From (3.11)–(3.13), we can find that $1-\theta$ and $1-\theta(1-\lambda)$ are common factors in all the optimal responses. Small investors are more sensitive to private and public signals (ψ_x and ψ_z, respectively) when they put less weight on others' actions (lower beauty contest parameter θ or lower weight on the averaged small investors' action $\theta(1-\lambda)$). On the other hand, the large investor's action (ψ_l) has a more impact on small investors when they consider others' actions (higher θ) or the market share of the large investor is significant (higher λ).

In emerging markets, it is more difficult to observe the fundamentals due to the limited available information than in advanced markets. Hence, investors put more weight on others' actions, implying higher θ. As θ increases, small investors rely more on the large investor's action (ψ_l), yet less on private and public information (ψ_x and ψ_z). It can lead to a higher level of herding among small investors in emerging markets.

In the model, the large investor's action l and public information z lead small investors to move in the same direction because those signals are common to all small investors. In contrast, the private information of small investors x_j generates idiosyncratic movements. Therefore, the coefficients ψ_l and ψ_z relative to ψ_x present the degree of herd behavior in the market.

Let us denote the small investor's reaction ratio of the private to the public signal in order to understand the herd behavior among small investors.

$$\ln \frac{\psi_x}{\psi_z} = \ln[1-\theta(1-\lambda)] + \ln \frac{\alpha_x}{\alpha_z} = \ln[1-\theta(1-\lambda)] + \ln \frac{\sigma_z^2}{\sigma_x^2}, \tag{3.14}$$

The log ratio indicates how much the small investor is more sensitive to private signals than to public information. Hence, small investors are likely to follow others' behavior more based on common knowledge as the ratio decreases, which means herd behavior.

The small investor's relative response to a private signal (ψ_x/ψ_z) is less sensitive compared to the signal-extraction equilibrium (ψ_x^{se}/ψ_z^{se}) since the investor takes others' actions into account in the beauty contest game. Moreover, the relative accuracy of information also affects the relative reaction ratio. As the private signal gets more accurate than the public signal (higher σ_z^2/σ_x^2), the small investor becomes more sensitive to the private signal (higher ψ_x/ψ_z). The following lemma states it formally.

Lemma 1 *Given the beauty contest parameter $\theta \in (0,1)$, the small investor's optimal action satisfies:*

$$\frac{\psi_x}{\psi_z} \leq \frac{\alpha_x}{\alpha_z} = \frac{\psi_x^{se}}{\psi_z^{se}} \quad \textit{and} \quad \frac{\partial \ln(\psi_x/\psi_z)}{\partial \ln(\alpha_x/\alpha_z)} = \frac{\partial \ln(\psi_x/\psi_z)}{\partial \ln(\sigma_z^2/\sigma_x^2)} = 1.$$

Proof. See Appendix I. ■

Now, to see how the large investor's market share (λ) shapes the small investor's optimal action (s_j), first let us consider the two limiting cases on market concentration, perfect competition, and monopoly (labeled by *pc* and *mo*, respectively). In perfect competition, the large investor has zero measure and only provides public information. In a monopoly, on the other hand, the large investor dominates the market. Then, we obtain

$$s_j^{pc} = \lim_{\lambda \to 0} s_j^* = \left(\frac{1-\theta}{1-\theta\alpha_x}\right)\alpha_x x_j + \left(\frac{1}{1-\theta\alpha_x}\right)\alpha_z z = \psi_x^{pc} x_j + \psi_z^{pc} z, \tag{3.15}$$

$$s_j^{mo} = \lim_{\lambda \to 1} s_j^* = (1-\theta)\alpha_x x_j + (1-\theta)\alpha_z z + \theta l = \psi_x^{mo} x_j + \psi_z^{mo} z + \psi_l^{mo} l. \tag{3.16}$$

Small investor j's reaction to the private signal (ψ_x) in both limiting cases is smaller than that of the signal extraction equilibrium when there is no strategic behavior ($\psi_x^{pc}, \psi_x^{mo} \leq \psi_x^{se}$). This is because investors consider not only the private signal but also public information and hence the importance of the private signal shrinks. Furthermore, as the large investor's market share, λ, increases, the private information channel becomes less important since the observable large investor's action, l, plays a critical role in the market. It implies that $\psi_x^{mo} \leq \psi_x^{pc}$ $(\leq \psi_x^{se})$[6].

Public information is important for small investors to capture the fundamentals. And it is also useful to predict other investors' behavior since the public signal is disseminated across all the investors. As the market share of the large investor (λ) decreases, small investors sensitively respond to the public information (z) because investors rely less on the large investor's action (l) but more on the averaged small investor's strategy ($\bar{s}$). In perfect competition ($\lambda = 0$), small investors put more weight on the average others' action since the large investor is just like one of the small investors (high ψ_z^{pc}). When the large investor dominates the market ($\lambda = 1$), however, investors are sensitive to the large investor's behavior (l) rather than public information (low ψ_z^{mo}). Hence, $\psi_z^{mo} \leq \psi_z^{pc}$[7].

Now, consider the general case when $0 < \lambda < 1$. The reaction to the private and public signals (ψ_x and ψ_z, respectively) decreases with the large investor share (λ) while the response to the large investor's action (ψ_l) increases with increasing the large investor share. The following proposition summarizes the small investor's optimal responses to the states when there exists a large investor.

Proposition 1 *Given the beauty contest parameter $\theta \in (0,1)$, the small investor's optimal*

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[6]Since θ and α_x are smaller than 1, $1-\theta \leq 1$ and $(1-\theta)/(1-\theta\alpha_x) \leq (1-\theta)$. Thus, $\psi_x^{mo} = (1-\theta)\alpha_x \leq \alpha_x = \psi_x^{se}$ and $\psi_x^{pc} = (1-\theta)\alpha_x/(1-\theta\alpha_x) \leq (1-\theta)\alpha_x = \psi_x^{mo}$. To sum up, $\psi_x^{mo} \leq \psi_x^{pc} \leq \psi_x^{se}$.

[7]Since θ and α_x are smaller than 1, $1-\theta \leq 1$ and $1/(1-\theta\alpha_x) \geq 1$. Thus, $\psi_x^{mo} = (1-\theta)\alpha_z \leq \alpha_z = \psi_z^{se}$ and $\psi_z^{pc} = \alpha_z/(1-\theta\alpha_x) \geq \alpha_z = \psi_z^{se}$. To sum up, $\psi_z^{mo} \leq \psi_z^{se} \leq \psi_z^{pc}$.

action satisfies:

$$\frac{\partial \psi_x}{\partial \lambda} < 0, \quad \frac{\partial \psi_z}{\partial \lambda} < 0, \quad \textit{and} \quad \frac{\partial \psi_l}{\partial \lambda} > 0.$$

Proof. See Appendix I. ■

Proposition 1 presents that the large investor plays a critical role in that her action has a significant impact on small investors as in Corsetti et al. (2004). The market dominance of the large investors reduces the effect of private and public signals on small investors but strengthens the reaction to the large investor's action. Furthermore, it implies that herd behavior among small investors is derived from the large investor.

In the model, the large investor's action l and information z lead small investors to co-move together while the private information of small investors x_j generates idiosyncratic movements. It means that ψ_l and ψ_z relative to ψ_x indicate the degree of herd behavior in the market. However, the response of the large investor's share on the large investor's action and public information is the opposite. For example, the effect of the large investor's action on small investors increases with a higher share of the large investor, but small investors respond less to public information. Thus, the comparison of the magnitudes between both effects is needed to analyze the relationship between the market share of the large investor and herd behavior among small investors[8].

Corollary 1 *Given the beauty contest parameter $\theta \in (0,1)$, the small investor's optimal action satisfies:*

$$\frac{\partial \ln(\psi_l/\psi_z)}{\partial \ln \lambda} = 1 + \frac{\theta \lambda \alpha_x}{1 - \theta(1-\lambda)\alpha_x} \geq 1.$$

Proof. See Appendix I. ■

[8]The relative magnitude of both effects can be formally described in the log ratio as follows:

$$\ln \frac{\psi_l}{\psi_z} = \ln \frac{\lambda\theta[1 - \theta(1-\lambda)\alpha_x]}{(1-\theta)\alpha_z}$$

Corollary 1 implies that the more concentrated large investor causes a high level of herd behavior among small investors. That is, the effect of the large investor's share on the large investor's action is stronger than that on public information. Thus, a higher market share of the large investor increases the response to the large investor's action, leading small investors to follow the large investor.

To summarize, the presence of the large investor encourages small investors to move in the same direction, and the herding is intensified as the large investor becomes more dominant. Especially in emerging markets, the market is dominated by a few large investment managers, implying a higher λ. Higher concentrations increase the dependence of small investors on the large investor, resulting in a higher level of herding among small investors. This result provides a policy implication that market concentration is a critical factor to determine the herding in emerging markets.

3.4 Strategy of Large Investor[9]

Suppose the large investor's payoff is also the quadratic sum of distances of her action (l) to the fundamentals (f) and the average action ($\lambda l + (1-\lambda)\bar{s}$) in the market as in the small investor's payoff (3.1). The large investor's action (l) affects the market average action ($\lambda l + (1-\lambda)\bar{s}$) as much as λ. Also, the small investor's average action ($\bar{s}$) responds to the large investor's action (l). In particular, an increase in l leads to all small investors' action (s_j) increases by ψ_l. Thus, the large investor's payoff is described as follows.

$$u_1(l; f, \bar{s}(l)) \equiv -(1-\theta)(l-f)^2 - \theta[l - \lambda l - (1-\lambda)\bar{s}(l)]^2, \tag{3.17}$$

where $\bar{s}(l) = \psi_x \int_{[0,1)} x_j dj + \psi_z z + \psi_l l$ and $\int_{[0,1)} x_j dj = f$.

[9]The detailed derivations and proofs are in Appendix I.

Then, we can derive the following first order condition[10],

$$
\begin{aligned}
l &= \frac{(1-\theta)\mathbb{E}_1[f] + \theta(1-\lambda)^2(1-\psi_l)^2\{\psi_x\mathbb{E}_1[f] + \psi_z z\}}{(1-\theta) + \theta(1-\lambda)^2(1-\psi_l)^2} \\
&= \left[1 - \frac{\theta(1-\lambda)^2(1-\psi_l)^2\psi_l}{(1-\theta) + \theta(1-\lambda)^2(1-\psi_l)^2}\right]\beta z.
\end{aligned} \tag{3.18}
$$

As in equation (3.18), the optimal strategy of the large investor is a linear function of the public information z. It is shown that the large investor chooses her optimal action below the belief on the fundamentals[11]. The large investor perceives the presence of other investors, leading to a gap between the belief in the fundamentals and the optimal action. And the gap is closely related to the market share of the large investor λ - as the dominance of the large investor increases, the gap is smaller. For example, when the large investor has monopoly power ($\lambda = 1$), l equals βz which is exactly the same as the belief on the fundamentals since the investor doesn't need to consider small investors.

3.5 Conclusion

It is often observed that a few large investors dominate the market and small investors tend to follow the large ones in the financial markets. I introduce the simple sequential model in the spirit of Morris and Shin (2002), where investors' payoffs depend on market fundamentals and other investors' actions. Also, I assume that the market consists of a single large investor and a continuum of small investors, and a large one moves first, as in Corsetti et al. (2004). The model shows that small investors tend to follow the large investor more as the market share of the large one is higher under the assumptions. Especially in emerging markets where the information is less disclosed and markets are more concentrated, small investors are more

[10] The detailed derivation is in Appendix I.2

[11] Since $0 < \theta,\ \lambda,\ \psi_l < 1$,

$$
\left[1 - \frac{\theta(1-\lambda)^2(1-\psi_l)^2\psi_l}{(1-\theta) + \theta(1-\lambda)^2(1-\psi_l)^2}\right] < 1 \quad \Longleftrightarrow \quad l < \beta z = \mathbb{E}_1[f]
$$

likely to follow the action of the large investor, leading to a higher level of herding.

This chapter contributes to providing the relationship between investors of different sizes by adding the heterogeneity in investors' size to the beauty-contest game Morris and Shin (2002) introduces. And this model supports the fact that the level of herding is closely related to the market concentration.

In future studies, the micro-foundation to derive the payoff function is necessary to be implemented. Also, calibration work based on the model will be useful to check if it is better for small investors to follow the preceding action of the large investor.

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Appendix A

THE ADDITIONAL PROPERTIES OF HERDING MEASURE

A.1 Herding Measure for All the Funds including Passive Funds

The LSV herding measures for all the equity funds including active and passive funds are presented slightly higher than that for only the active funds. Passive funds are managed by the market index automatically and hence their co-movement reinforces the degree of herding. However, the difference in herding measures is not large due to the small fraction of passive funds.

Table A.1: Average Herding Measure by Investor's Size

		Sub-Period			All Period
		Pre GFC	GFC	Post GFC	
Large Investors		4.35	3.26	5.97	5.19
Small Investors	Total	8.14	7.65	9.20	8.77
	90–100th Percentile	5.88	4.69	6.00	5.83
	75–89th Percentile	4.50	5.72	6.40	5.86
	0–74th Percentile	6.82	6.08	7.88	7.43

Notes: 1. Presented in the table are values of H_t averaged of herding measure, H_{it}, across all countries for the given periods and groups. For example, the value of H_t shown in the first row, second column, is the average of H_{it} of 20 countries for 7 large investors during the pre-global financial crisis. The pre-GFC, GFC, and post-GFC periods are 2003.2–2007.6, 2007.7–2009.5, and 2009.6–2018.12, respectively. Small investors are grouped by size distribution. For example, the fourth row, 75–89th, means small investors whose equity investment is between 75 and 89 percentile of the size distribution.
2. The herding measure, H_{it}, is calculated considering not only active funds but also passive funds.

Table A.2: Average Herding Measure (%) by Investor Portfolio

	All	Pre GFC	GFC	Post GFC
Highly deviated (> 75th)	2.76	2.72	0.66	3.04
Moderately deviated (75 - 25th)	7.24	6.64	6.30	7.64
Lowly deviated (0 - 25th)	7.44	6.63	6.50	7.91

Note: 1. Investors are grouped by how much the investment share for each country is alike to the average share of all the small investors. The portfolio measure of small investor i, pf_i is calculated by $\sum_{j=1}^{20}(share_{ij} - \overline{share_j})^2$. And small investors are partitioned into 3 groups that are highly deviated, moderately deviated, and lowly deviated investors from the average portfolio. Investors whose portfolio measure is higher than the top 25 percentile are defined as highly deviated investors, and moderately deviated and lowly deviated investors have 25 to 75 percentile and bottom 25 percentile measures, respectively.
2. The herding measure, H_{it}, is calculated considering not only active funds but also passive funds.

Table A.3: Average Herding Measure (%) by Country

	BRA	CHL	CHN	COL	CZE	HUN	IDN	IND	ISR	KOR
Small Investors	11.25	5.35	9.91	6.23	8.37	8.99	8.63	8.39	8.67	10.70
	(9.56)	(8.66)	(9.72)	(9.74)	(9.79)	(9.78)	(9.56)	(9.07)	(10.65)	(8.84)
Pre GFC	10.34	3.33	7.04	5.19	5.29	7.63	8.02	7.32	9.27	13.09
(03.2-07.5)	(8.52)	(7.52)	(8.21)	(10.29)	(7.01)	(9.22)	(10.00)	(7.89)	(9.15)	(9.98)
GFC	10.71	6.28	10.93	3.95	9.19	7.73	6.04	7.17	7.83	8.58
(07.6-09.5)	(8.14)	(11.15)	(9.06)	(10.95)	(10.50)	(11.62)	(8.63)	(7.97)	(10.23)	(7.54)
Post GFC	11.78	6.07	10.99	7.18	9.59	9.87	9.45	9.14	8.57	10.05
(09.6-18.12)	(10.29)	(8.48)	(10.28)	(9.17)	(10.46)	(9.60)	(9.51)	(9.75)	(11.41)	(8.38)

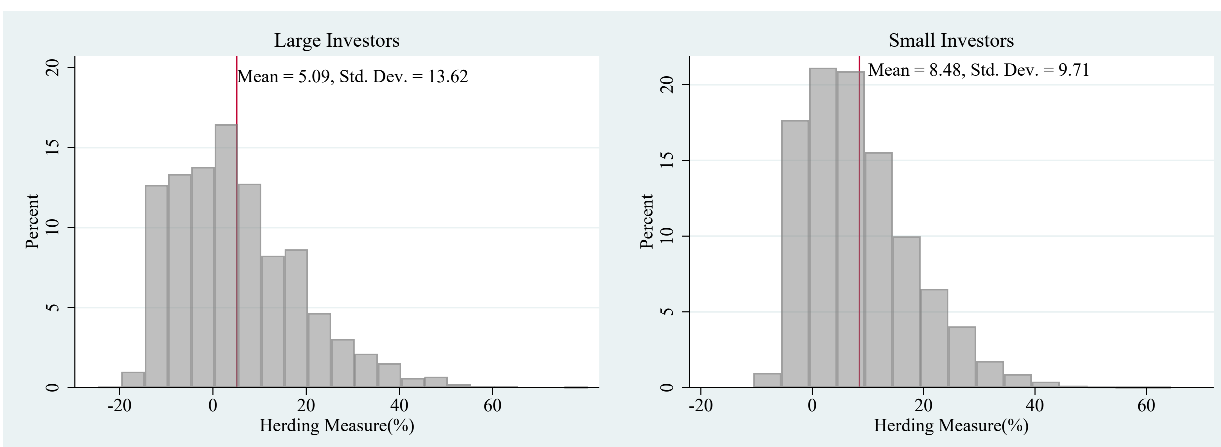
	MEX	MYS	PER	PHL	POL	RUS	THA	TUR	TWN	ZAF
Small Investors	7.25	7.45	8.35	7.78	7.83	12.37	8.24	10.95	10.00	7.15
	(8.85)	(9.48)	(10.75)	(9.98)	(8.45)	(10.64)	(9.61)	(11.46)	(9.79)	(8.78)
Pre GFC	5.64	9.69	5.73	9.67	7.21	11.60	9.31	9.24	11.99	6.99
(03.2-07.5)	(6.67)	(10.37)	(7.94)	(11.41)	(8.25)	(11.23)	(11.89)	(9.34)	(10.10)	(8.79)
GFC	6.44	7.99	6.67	6.21	8.00	14.01	3.88	7.30	8.22	6.21
(07.6-09.5)	(8.79)	(10.14)	(9.66)	(10.41)	(8.72)	(9.99)	(7.33)	(10.28)	(9.33)	(9.45)
Post GFC	8.15	6.32	9.89	7.25	8.07	12.38	8.67	12.49	9.48	7.43
(09.6-18.12)	(9.64)	(8.79)	(11.80)	(9.14)	(8.54)	(10.54)	(8.66)	(12.33)	(9.69)	(8.69)

standard deviation in parentheses
Note: 1. The average herding measure for each country is calculated within the group. For example, the value of $\overline{H}_{it}$ shown in the second row, third column, is the average of H_{it} for small investors who invest in China during the pre-global financial crisis (2003.2-2007.6).
2. The herding measure, H_{it}, is calculated considering not only active funds but also passive funds.

A.2 Distribution

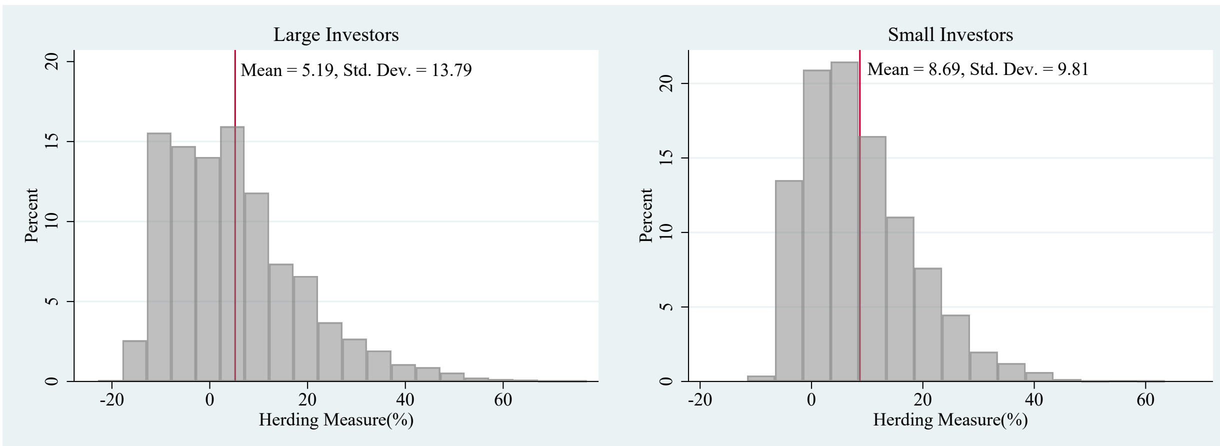
Figure A.1 shows the distribution of LSV herding measures of large and small investors when considering only active funds. Both distributions are right-skewed because they are assumed by a binomial process. Although it presents a similar shape, the average herding scale of small investors (8.48%) is larger than that of large investors (5.09%). This means that small investors tend to flock together more than large investors. Also, both graphs indicate that the herding measure is widely dispersed, implying the herding measure tends to fluctuate significantly across countries and months. The standard deviation of large investors is larger than the standard deviation of small investors since the number of large investors is much smaller, resulting in greater volatility.

Figure A.1: Herding Measure Distribution of Large and Small Investors for Active Funds



Including active as well as passive funds, LSV herding measures show a slight increase for both large and small investors, as shown in Figure A.2. It means that the presence of passive funds reinforces the degree of herd behavior since the movement of passive funds is automatically driven by the market indices. However, the distribution in Figure A.2 is quite similar to Figure A.1 which considers only the active funds.

Figure A.2: Herding Measure Distribution of Large and Small Investors for All Funds



A.3 Additional Results of the LSV Herding Measure

A.3.1 Herding by Investor's Portfolio

Table A.4: Average Herding Measure (%) by Investor Portfolio

	All	Pre GFC	GFC	Post GFC
Highly deviated (> 75th)	2.70	2.68	1.69	2.83
Moderately deviated (75 - 25th)	6.92	6.56	6.06	7.23
Lowly deviated (0 - 25th)	7.14	6.54	6.42	7.53

Notes: 1. Investors are grouped by how much the investment share for each country is alike to the average share of all the small investors. The investment share is the percentage of equity investment to a particular country j over total equity investment conducted by investor i. The portfolio measure of investor i for country j is calculated by $\sum_{j=1}^{20}(share_{ij} - \overline{share}_j)^2$. And small investors are partitioned into 3 groups that are highly deviated, moderately deviated, and lowly deviated investors from the average portfolio. Investors whose portfolio measure is higher than the top 25 percentile are defined as highly deviated investors, and moderately deviated and lowly deviated investors have 25 to 75 percentile and bottom 25 percentile measures, respectively.
2. The herding measure is calculated only considering the active funds. The table for the average LSV herding measure when including all the funds is exhibited in Appendix A.

Table A.4 shows the average herding measure by investors' portfolio tendency. Investors show a different portfolio choice and it might affect the herd behavior. I consider how much the investment share for each country deviated from the average share of all the small investors as the measure of the portfolio choice of each investor and partitioned into 3 groups depending on the deviation. As in Table A.4, highly deviated investors from the average portfolio trend show a low herding measure (2.76%), while significant herd behavior is observed for the other investors (larger than 7%). Among the other investors, the herding measure of lowly deviated investors is slightly higher than that of moderately deviated investors. And this trend is consistent across the period.

In general, highly deviated investors tend to determine the investment on their own information and decision rules rather than relying on others' behavior, and it makes their portfolio deviate from the others more. On the other hand, investors who tend to imitate others' behavior show a similar portfolio choice, which presents a relatively high herding measure.

A.3.2 Herding by Investment Pattern

In the equation (1.1), we define the herd behavior happens when investors simultaneously increase more than the average increase ($p_{it} - p_t > 0$) or decrease more than the average decrease ($p_{it} - p_t < 0$). That is, there are two kinds of herding patterns - increase and decrease, and they might show the different aspects of herd behavior. In order to segregate the herding effect by the pattern, the LSV measure in (1.1) is modified by partitioning into two groups depending on the pattern and calculating within each group as follows (Grinblatt et al., 1995; Wermers, 1999; Bellando, 2010).

$$IH_{it} = H_{it}|_{p_{it}-p_t>0} \tag{A.1}$$

$$DH_{it} = H_{it}|_{p_{it}-p_t<0} \tag{A.2}$$

where IH_{it} (DH_{it}) is the herding measure for the increase (decrease) pattern.

Table A.5 presents the LSV herding measure depending on the investment pattern. Dis-

Table A.5: Average Herding Measure (%) by Equity Change: Increases and Decreases

	Large Investors			Small Investors		
	H_{it}	IH_{it}	DH_{it}	H_{it}	IH_{it}	DH_{it}
Total	5.09	7.66	7.29	8.53	8.97	9.43
Pre GFC	4.42	6.99	6.14	8.05	7.80	9.75
GFC	3.84	6.03	6.33	7.50	8.56	7.51
Post GFC	5.65	8.31	8.01	8.90	9.49	9.64

Notes: 1. All the equity investments break into two patterns - increase and decrease. The herding measure is calculated separately by pattern. IH_{it} presents the LSV measure (H_{it}) when the increase ratio of equity investment is higher than the average ratio ($p_{it} - p_t > 0$) while DH_{it} indicates the measure when the equity fund decreases more than the average level ($p_{it} - p_t < 0$). Presented in the table are values of averaged herding measures across all countries for the given periods and patterns.
2. The herding measure is calculated for only small investors and only considers the active funds.

aggregating by the pattern, each segregated herding measure, IH_{it} and DH_{it}, is around 7 – 9 percent, respectively, which is higher than the overall measure, H_{it}. And the herding measure of the increase, IH_{it}, is not much different from that of the decrease, DH_{it}, implying they show a similar degree of herd behavior.

Taking a closer look at Table A.5, however, the different aspect is exhibited depending on the large and small investors. For large investors, the herding measure of the increase is slightly higher than that of the decrease, meaning that large investors are more likely to herd when they increase investment in equity funds. On the other hand, small investors show a little higher herding measure of decrease than that of increase, which implies that they tend to herd more when decreasing equity investment. We can interpret this result as large investors are more prudent when increasing their investment and hence they tend to consider and mimic other investors' behavior. Small investors, in contrast, are likely to follow others' decrease in equity investment in order to avoid the loss due to simultaneous withdrawal. This is because small investors are easily affected by others' investment decisions and are vulnerable to that risk while large investors have dominance of the equity market so they can manage the risk.

Table A.6: Average Herding Measure (%) by Country

	BRA	CHL	CHN	COL	CZE	HUN	IDN	IND	ISR	KOR
Small Investors	11.07	5.20	9.80	5.87	7.76	8.66	8.51	8.45	8.61	10.73
	(9.46)	(8.47)	(9.69)	(9.56)	(9.33)	(10.18)	(9.41)	(9.06)	(10.62)	(8.89)
Pre GFC	10.18	3.62	7.22	5.09	5.45	7.40	7.58	7.63	9.14	13.13
(03.2-07.5)	(8.47)	(7.35)	(8.20)	(10.41)	(6.60)	(9.50)	(9.72)	(8.00)	(9.13)	(10.06)
GFC	10.20	6.80	10.96	3.67	8.28	7.48	5.81	6.82	7.42	8.40
(07.6-09.5)	(7.97)	(11.50)	(9.03)	(10.96)	(9.52)	(11.59)	(8.24)	(7.69)	(9.89)	(7.78)
Post GFC	11.65	5.58	10.73	6.68	8.70	9.48	9.50	9.16	8.62	10.12
(09.6-18.12)	(10.17)	(8.18)	(10.29)	(8.82)	(10.20)	(10.18)	(9.42)	(9.75)	(11.43)	(8.38)
	MEX	MYS	PER	PHL	POL	RUS	THA	TUR	TWN	ZAF
Small Investors	7.14	7.38	8.08	7.76	7.16	12.22	8.24	10.69	9.82	6.50
	(8.73)	(9.28)	(10.55)	(9.72)	(8.55)	(10.44)	(9.46)	(11.28)	(9.57)	(8.55)
Pre GFC	5.55	9.40	5.45	9.69	6.86	11.57	9.40	8.89	11.87	6.88
(03.2-07.5)	(6.63)	(10.38)	(7.43)	(11.64)	(8.20)	(10.94)	(11.74)	(9.66)	(9.93)	(8.76)
GFC	6.24	8.43	6.55	5.88	7.43	14.03	4.12	7.26	8.03	6.23
(07.6-09.5)	(8.64)	(9.43)	(9.84)	(10.32)	(8.31)	(9.66)	(7.47)	(9.98)	(9.34)	(9.33)
Post GFC	8.05	6.25	9.59	7.28	7.24	12.14	8.58	12.23	9.27	6.38
(09.6-18.12)	(9.49)	(8.61)	(11.63)	(8.53)	(8.82)	(10.41)	(8.49)	(11.99)	(9.38)	(8.36)

standard deviation in parentheses

Notes: 1. The average herding measure for each country is calculated within the group. For example, the value of $\overline{H}_{it}$ shown in the second row, third column, is the average of H_{it} for small investors who invest in China during the pre-global financial crisis (2003.2-2007.6).

2. The herding measure is calculated only considering the active funds. The table for the average LSV herding measure when including all the funds is exhibited in Appendix A.

I also analyze the herding measure of small investors by country. From Table 1.2 and A.6, I find the relation between the size of equity investment and the herding measure. The herding measure is shown strikingly higher in the countries where the investment size of equity investment is greater such as Brazil, China, South Korea, Russia, and Taiwan. It implies that the investors become more risk-averse as the size of the equity fund increases and hence they tend to consider and mimic the other investors more.

A.3.3 Persistence in Herding

Moreover, I revisit another approach that Barber et al. (2009) propose to test if the herd behavior among small investors is observed in a contemporaneous and intertemporal manner. I partitioned small investors into two equal groups of investors randomly and calculated the percentage of the equity fund increases among all the equity investment changes for each country in each month. Based on each percentage, I compute the correlation with lags $L = 0, 1, \ldots, 12$ within each group and between two groups. Then, the contemporaneous correlation ($L = 0$) between groups 1 and 2 implies the degree of herd behavior and the time-series correlation ($L = 1, \ldots, 12$) displays how long the herding persists.

Table A.7 presents the mean contemporaneous and time-series correlation of percentage increases across investor groups. First, the contemporaneous correlation between groups 1 and 2 indicates 85.7 percent with significant t values, which implies a high degree of herding among small investors. This is consistent with the outcome of the LSV herding measure in Figure 1.5 or Table 1.3. However, herd behavior does not seem to be persistent according to the time-series correlations and t-statistics. The highest intertemporal correlation is at most around 11 percent and most values are below 1–2 percent. Also, almost t-values are below 1.96, implying the insignificance of correlation at a 5% significance level. In conclusion, we can find other evidence of significant herding among small investors according to Barber et al. (2009) even if it is constrained only in that period.

It is natural to ask whether herd behavior relates to market and macro variables. To answer this question, Appendix B shows the panel regression including pull and push factors, as explanatory variables to analyze the herding measure. Table B.1 reports the regression results.

Table A.7: Mean contemporaneous and time-series correlation of percentage increases by individual investors

Horizon (L)	Correlation of % increases in month t with % increases in month $t+L$			t-statistics		
	Group 1 with group 1	Group 2 with group 2	Group 1 with group 2	Group 1 with group 1	Group 2 with group 2	Group 1 with group 2
0	100.0%	100.0%	85.72%	N.A.	N.A.	10.16
1	9.35%	11.15%	10.99%	1.52	1.46	2.10
2	3.05%	2.68%	3.99%	0.54	0.57	0.66
3	8.01%	8.35%	8.73%	1.38	1.98	1.67
4	0.42%	2.10%	2.63%	0.07	0.37	0.41
5	-0.62%	0.98%	-0.08%	-0.14	0.24	-0.02
6	3.00%	0.95%	2.99%	0.45	0.12	0.42
7	0.16%	0.95%	0.83%	0.03	0.20	0.19
8	0.93%	0.30%	0.29%	0.13	0.04	0.04
9	0.11%	0.32%	0.77%	0.02	0.05	0.12
10	1.97%	1.16%	2.44%	0.34	0.16	0.39
11	-0.05%	-1.49%	-0.68%	-0.01	-0.16	-0.08
12	-0.60%	-0.63%	-0.04%	-0.10	-0.08	0.00

Notes: 1. Revisiting the Barber et al. (2009), I partitioned small investors into two equal groups of investors randomly. For each country in each month, I calculate the percentage of all equity investment increases. The first row indicates the contemporaneous correlation between the two groups and the remaining rows present the time-series correlation from one month to 12 months. The third column provides the correlation between the percentage increases by group 1 at time t and the percentage increases by group 2 at time $t+L$ where $L = 1, \ldots, 12$. t-statistics are based on the mean and standard deviation of the calculated correlations.
2. The herding measure is calculated for only small investors and only considers the active funds.

Appendix B
HERDING FACTOR ANALYSIS

B.1 Model

The degree of herding is affected by a number of factors and the herding measure has been analyzed by the factors that have an impact on stock trading such as past return, P/E ratio, and volatility measure (Hsieh et al. (2020), Zhou and Lai (2009)). In this paper, I examine the herding of the equity flow across the border instead of herd behavior in stock trading, and hence I apply the other factors - pull and push factors - that are widely used in the literature on capital flows (Hannan (2017), Koepke (2019)). The pull factor is a domestic feature that reflects the economic fundamental of the county (i.e. GDP growth rate, interest rate, and stock market index of the country). The push factor is external conditions that underpin the supply of global liquidity (i.e. global risk premium, GDP growth rate, and interest rate of the advanced economy). Both pull and push factors affect equity fund investment. Including these factors, the panel regression model is established as follows.

$$Y_{it} = Y_{i(t-1)} + \boldsymbol{\beta}_{pull}\mathbf{pull}_{it} + \boldsymbol{\beta}_{push}\mathbf{push}_t + \xi_i + \xi_t + \epsilon_{it} \tag{B.1}$$

The dependent variable Y_{it} is the overall LSV herding measure (H_{it}) or the measure depending on the patterns (IH_{it} or DH_{it}) in the emerging country i at time t, and $Y_{i(t-1)}$ is the control variable for the herding measure at the previous time $t-1$. **pull** (pull factor) includes the real interest rate, the growth rate of industrial production, the growth rate of the total reserve, the growth rate of the exchange rate, and the growth rate of the stock market index for each emerging country while **push** (push factor) involves U.S. real interest rate, the growth rate of VIX, the growth rate of U.S. industrial production, and growth rate of U.S. stock market index (Dow Jones Industrial Average) are used for push factors. ξ_i is fixed effects to control unobserved heterogeneity of emerging markets, and ξ_m is to control months for removing the seasonality.

B.2 Results

Table B.1 shows the result of the regression (B.1). Overall, regressions (1) and (2) present that unfavorable conditions for emerging markets increase herd behavior. It implies that, in negative conditions, small investors confront restricted information availability and more risk aversion brought by uncertainty, leading to imitating others' behavior. To be more specific, for pull factors, the negative domestic conditions - a decrease in the growth rate of the total reserve, an increase in the growth rate of the exchange rate, and a decrease in the growth rate of the stock market index - lead to a higher level of herding. On the other hand, the relation between push factors and herding is not consistent. Both unfavorable and favorable external conditions seem to be related to the level of herding. For instance, both the increase in US industrial production growth rate (positive condition) and the decrease in the US stock market index growth rate (negative condition) encourage small investors to herd more simultaneously. Despite the ambiguity of push factors' effect, unfavorable domestic conditions strengthen herd behavior among small investors.

Disaggregating the equity investment patterns, each regression shows a similar result to the overall regression including the impact of the growth rate of the exchange rate and the stock market index. One intriguing finding is the effect of domestic and US real interest rates on the LSV herding value of each pattern. In the increasing period of equity investment, the domestic real interest rate has a positive impact on the measure while the effect of the US real interest rate is not significant. A higher real interest rate leads to a higher degree of herd behavior when small investors increase equity funds to emerging countries simultaneously. On the other hand, US real interest rate plays a significant role in promoting the degree of herding during the decreasing period while the domestic real interest rate does not have an impact on the herding measure.

Table B.1: LSV Herding Measure Regression Results

	LSV Measure (%)					
	H_{it}		IH_{it}		DH_{it}	
	(1)	(2)	(3)	(4)	(5)	(6)
Real Interest Rate (%)	-0.005	-0.011	0.018	0.123**	-0.007	-0.010
	(0.010)	(0.025)	(0.012)	(0.051)	(0.012)	(0.027)
ΔIndustrial Production	-0.004	-0.004	-0.009	-0.009	-0.006	-0.006
	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
ΔTotal Reserve	-0.051***	-0.051***	-0.057**	-0.065**	-0.043	-0.044
	(0.016)	(0.016)	(0.022)	(0.026)	(0.031)	(0.031)
ΔExchange Rate	0.054***	0.053***	0.062**	0.060**	0.065***	0.065***
	(0.013)	(0.013)	(0.029)	(0.027)	(0.017)	(0.017)
ΔStock Market Index	-0.040***	-0.041***	-0.075***	-0.077***	-0.061***	-0.061***
	(0.009)	(0.009)	(0.015)	(0.015)	(0.014)	(0.014)
US Real Interest Rate (%)	-0.053***	-0.051***	-0.003	-0.006	0.407***	0.408***
	(0.011)	(0.013)	(0.016)	(0.020)	(0.017)	(0.018)
ΔUS Industrial Production	0.370***	0.371***	-0.201***	-0.206***	0.675***	0.675***
	(0.015)	(0.015)	(0.040)	(0.040)	(0.037)	(0.037)
ΔUS Stock Market Index	-0.046***	-0.046***	-0.181***	-0.184***	-0.148***	-0.148***
	(0.006)	(0.006)	(0.016)	(0.018)	(0.010)	(0.010)
ΔVIX	-0.023***	-0.023***	-0.015***	-0.015***	-0.032***	-0.032***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	355420	355420	355420	355420	355420	355420
R-squared	0.081	0.081	0.227	0.233	0.127	0.127

Standard errors are in parentheses. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)
Notes: 1. The dependent variables include the overall LSV measure ((1) and (2)), and the herding measure depending on the patterns ((3) and (4) are the value for the increase, and (5) and (6) is the one for the decrease). The regressions are estimated across all the periods (2003.2-2018.12) and fixed effects are included in all the regressions. And the LSV measure is calculated only for small investors.
2. The herding measure is calculated for only small investors and only considers the active funds.

Appendix C

THE RESULTS OF PANEL REGRESSION FOR ALL EQUITY FUNDS

Table C.1: Panel Regression Result - Large/Small Investors' Effect

	100 × Log Investment			
	(1)	(2)	(3)	(4)
Large Investors' Effect (%)	0.129***	0.097***	0.131***	0.103***
	(0.038)	(0.034)	(0.037)	(0.033)
Small Investors' Effect (%)	-0.054	-0.074	-0.054	-0.073
	(0.060)	(0.060)	(0.059)	(0.058)
Pull/Push Factors	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	348680	347670	348680	347670
R-squared	0.944	0.944	0.945	0.945

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. All regressions include the log of previous equity investment, and the coefficients of the other variables are omitted in the table to focus on the large investors' effect. The interpretation of the other variables is explained in Section 1.5.3.

Table C.2: Large/Small Investors' Effect by Period

	100 × Log Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
Large Investors' Effect (%)	0.133**	0.152***	-0.100	-0.106*	0.134**	0.131***
	(0.059)	(0.052)	(0.058)	(0.060)	(0.047)	(0.042)
Small Investors' Effect (%)	0.051	0.002	-0.031	0.029	-0.135*	-0.116
	(0.087)	(0.089)	(0.126)	(0.118)	(0.077)	(0.070)
Period	Pre GFC	Pre GFC	GFC	GFC	Post GFC	Post GFC
Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	84100	84100	38240	38240	225330	225330
R-squared	0.941	0.942	0.920	0.922	0.950	0.951

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. The pre-GFC, during GFC, and post-GFC periods are 2003.2–2007.6, 2007.7–2009.5, and 2009.6–2018.12, respectively. All regressions include the log of previous equity investment and the other pull and push factors in the model 1.5, but the coefficients of those variables are omitted in the table to focus on the large investors' effect.

Table C.3: Large Investors' Effect by Investors' Size

	100 × Log Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
Large Investors' Effect (%)	0.240**	0.073	0.157**	0.106	0.203**	0.105**
	(0.108)	(0.087)	(0.056)	(0.080)	(0.097)	(0.039)
Small Investors' Effect (%)	-0.178	0.149	-0.018	-0.027	-0.012	-0.149*
	(0.308)	(0.163)	(0.099)	(0.112)	(0.158)	(0.082)
Period	Pre GFC	Pre GFC	Pre GFC	Post GFC	Post GFC	Post GFC
Investor Size	>90th	75−90th	0−75th	>90th	75−90th	0−75th
Observations	9280	12940	61880	24732	35324	165274
R-squared	0.926	0.955	0.933	0.963	0.940	0.941
	100 × Log Investment					
	(7)	(8)	(9)			
Large Investors' Effect[1] (%)	0.081	0.111*	0.101**			
	(0.063)	(0.062)	(0.037)			
Small Investors' Effect[1] (%)	-0.081	-0.020	-0.079			
	(0.111)	(0.168)	(0.062)			
Period	All	All	All			
Investor Size	>90th	75−90th	0−75th			
Observations	38292	54224	255154			
R-squared	0.947	0.941	0.936			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. The pre-GFC and post-GFC periods are 2003.2–2007.6 and 2009.6–2018.12, respectively. All regressions include the fixed effects, the log of previous equity investment, and the other pull and push factors in the model 1.5, but the coefficients of those variables are omitted in the table to focus on the large investors' effect. The rank of investor size is based on the size of equity investment among small investors, and I partitioned three groups of investor size (>90th, 75–90th, and 0–75th) based on the distribution of small investors' size.

Table C.4: Panel Regression Result - Pull/Push Factors

	100 × Log Investment			
	(1)	(2)	(3)	(4)
Real Interest Rate	0.151	0.510	0.169	0.394
	(0.175)	(0.331)	(0.152)	(0.307)
Δ Industrial Production	-0.111*	-0.090	-0.117*	-0.105*
	(0.059)	(0.054)	(0.059)	(0.056)
Δ Total Reserve	0.367**	0.312**	0.332**	0.273**
	(0.131)	(0.122)	(0.135)	(0.130)
Δ Exchange Rate	-0.785***	-0.780***	-0.806***	-0.799***
	(0.145)	(0.152)	(0.146)	(0.156)
Δ Stock Market Index	0.768***	0.759***	0.757***	0.747***
	(0.117)	(0.116)	(0.111)	(0.111)
US Real Interest Rate	-0.296	0.306	-0.248	0.268
	(0.287)	(1.221)	(0.328)	(1.224)
Δ US Industrial Production	-1.621**	-1.837**	-1.546**	-1.735**
	(0.620)	(0.672)	(0.622)	(0.664)
Δ US Stock Market Index	-0.078	-0.092	-0.100	-0.118
	(0.203)	(0.211)	(0.206)	(0.210)
Δ VIX	-0.023	-0.022	-0.024	-0.024
	(0.032)	(0.033)	(0.032)	(0.032)
Δ Exchange Rate$_{(t-1)}$		-0.307**		-0.358**
		(0.137)		(0.135)
Δ Exchange Rate$_{(t-2)}$		-0.231		-0.290*
		(0.147)		(0.147)
Δ Stock Market Index$_{(t-1)}$		0.198*		0.212*
		(0.114)		(0.114)
Δ Stock Market Index$_{(t-2)}$		-0.091		-0.071
		(0.061)		(0.069)
Lagged Variables	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	347670	346130	347670	346130
R-squared	0.944	0.944	0.945	0.945

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. All regressions include the log of previous equity investment and the large and small investors' effect, but only the coefficients of pull and push factors are presented in the table. I include all the lagged variables of pull and push factors but only those of exchange rate and stock market index are presented because the other lagged variables turn out to be insignificant.

Table C.5: Large Investors' Effect with Extraordinary Flows

	100 × Log Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
Large Investors' Effect × Dummy Variable						
$\lvert$Equity Growth$\rvert < 10\%$	0.008		0.023		0.037*	
	(0.013)		(0.034)		(0.019)	
$\lvert$Equity Growth$\rvert \geq 10\%$	0.349***		0.452***		0.439***	
	(0.112)		(0.144)		(0.178)	
$\lvert$Equity Growth$\rvert < 20\%$		0.004		0.027		0.022
		(0.011)		(0.033)		(0.017)
$\lvert$Equity Growth$\rvert \geq 20\%$		0.613***		0.801***		0.806**
		(0.200)		(0.262)		(0.328)
Period	All	All	Pre GFC	Pre GFC	Post GFC	Post GFC
Observations	355420	355420	85800	85800	230620	230620
R-squared	0.945	0.945	0.942	0.942	0.950	0.950

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are corrected for arbitrary correlation within investors and within countries (two-way clustered). In each regression, singleton observations are dropped. The pre-GFC and post-GFC periods are 2003.2–2007.6 and 2009.6–2018.12, respectively. All regressions include all the variables in the modified model 1.6, but the coefficients of those variables except for the interact term are omitted in the table to focus on the large investors' effect in extraordinary cases.

Appendix D
MULTINOMIAL LOGISTIC REGRESSION ANALYSIS

D.1 Model

The multinomial logistic regression model explains the fund manager's portfolio choice across emerging countries. It examines the factors to affect the portfolio choice of investors. Given the same assumption in Chapter 1 as the linear panel model, the multinomial logistic model is established as follows:

$$\ln \frac{w_{ict}}{w_{ic_0t}} = \rho \ln \frac{w_{ic(t-1)}}{w_{ic_0(t-1)}} + \boldsymbol{\beta}_{pull}\mathbf{pull}_{ct} + \boldsymbol{\beta}_{push}\mathbf{push}_t + \xi_i + \xi_c + \xi_m + \epsilon_{ict} \tag{4.4}$$

The dependent variable, $\ln \frac{w_{ict}}{w_{ic_0t}}$, is the log of odd ratio of investor i at time t. The odd ratio is the share of equity investment to a particular country c over the share of that to Peru. The share means the percentage of equity funds investment to country c over total equity investment conducted by fund manager i at time t[1]. And Peru is the anchor country to compare with other countries, and hence the higher odd ratio means the higher preference of country c relative to Peru.

$\ln \frac{w_{ic(t-1)}}{w_{ic_0(t-1)}}$ is the log of the odd ratio at the previous period, controlling for inertia. As in the analysis of the linear panel regression model in Chapter 1, I include pull and push factors as the drivers of equity flow in emerging markets. **pull** (pull factor) includes the real interest rate, the growth rate of industrial production, the growth rate of the total reserve, the growth rate of the exchange rate, and the growth rate of the stock market index for each emerging country while **push** (push factor) involves U.S. real interest rate, the growth rate

[1] For log calculation, I set a very small number ($1e-10$) for the zero shares.

of VIX, the growth rate of U.S. industrial production, and growth rate of U.S. stock market index (Dow Jones Industrial Average) are used for push factors. ξ_i and ξ_c are fixed effects to control unobserved heterogeneity of investors and emerging markets, respectively. And ξ_m is to control months for removing the seasonality.

In this model, I pin down the analysis of drivers that affect the portfolio choice across countries, and hence the impacts of large and small investors – the average equity funds investment of large and small investors in the previous month – are not included. Also, these prior large and small investors' behaviors are not consistent with the odd ratio which is the dependent variable in this model. In summary, without examining the relationship between large and small investors as in Chapter 1, I define the problem as which drivers have a significant impact on an investor's portfolio choice in emerging countries and apply a multinomial logistic regression model, also known as the demand approach, for analysis.

D.2 Result

As seen in Table D.1, the growth rate of the stock market index is the most significant driver for investors to determine their portfolio choice. It means that a higher stock market index of a particular country induces fund managers to invest more in the equity funds of the country than in other emerging countries. This is consistent with the outcome of the panel regression model in Table 1.7. Also, the growth rate of the total reserve is weakly significant, implying that a more sound total reserve is a good signal for investors to put their money into the equity funds of a particular emerging country. Meanwhile, the effect of push factors is insignificant except for the U.S. real interest rate. Given the fixed effect, U.S. real interest rate has a positive impact on investors' portfolio choices.

The difference from the result of linear panel regression in Table 1.7 is the insignificance of the growth rate of the exchange rate. In the panel model, two price factors, exchange rate, and stock market index, are the most critical drivers to determine the size of equity investment with the prior large investors' behavior. The growth rate of the exchange rate, particularly, has a negative influence on the investors' equity investment decisions not only for the current but also for the next period. With respect to the portfolio decision in which countries fund managers invest more, the growth rate of the exchange rate is not significant. In addition, an investor's portfolio choice is not affected by the growth rate of US industrial production, whereas it is significant in the linear panel model. Overall, pull and push factors excluding the growth rate of the stock market index are not meaningful to investors' portfolio choice problems.

Table D.1: Multinomial Logistic Regression Result

	Log of Odd Ratio			
	(1)	(2)	(3)	(4)
Real Interest Rate (%)	0.005	0.004	0.010	0.000
	(0.009)	(0.016)	(0.011)	(0.016)
Δ Industrial Production	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Δ Total Reserve	0.013**	0.012*	0.013*	0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
Δ Exchange Rate	-0.002	-0.002	-0.003	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Δ Stock Market Index	0.011**	0.011***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)
US Real Interest Rate (%)	0.024*	0.023	0.037**	0.036**
	(0.014)	(0.014)	(0.016)	(0.016)
Δ US Industrial Production	-0.002	-0.004	-0.002	-0.006
	(0.032)	(0.032)	(0.033)	(0.033)
Δ US Stock Market Index	0.013	0.015	0.012	0.013
	(0.010)	(0.010)	(0.010)	(0.010)
Δ VIX	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Δ Exchange Rate$_{(t-1)}$		0.003		0.002
		(0.005)		(0.004)
Δ Exchange Rate$_{(t-2)}$		-0.008		-0.010*
		(0.006)		(0.005)
Δ Stock Market Index$_{(t-1)}$		0.001		0.001
		(0.004)		(0.004)
Δ Stock Market Index$_{(t-2)}$		-0.002		-0.001
		(0.003)		(0.003)
Lagged Variables	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	362801	353843	362801	353843
R-squared	0.884	0.884	0.886	0.886

Notes: 1. Log of odd ratio = ln (share of equity investment to country c / share of equity investment to Peru),
Share = Percentage of equity investment to country c over total equity investment conducted by investor i at time t
2. Not only small investors but large investors are included when running the model.
Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix E

DATA COLLECTION

E.1 Dependent Variable

I gather portfolio weight from Country Allocations of the EPFR Global dataset (https://financialintelligence.informa.com/epfr). I collect all monthly equity funds (or bond funds) of the manager level during 2003-2015. I exclude developed countries and choose 20 emerging countries (Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey). I merge all the funds across the investors at each period and calculate the portfolio weight. And finally, I compute the odd ratio of portfolio weight by dividing the portfolio weight by the outside weight. The outside weight is 100 minus the sum of all the weight.

E.2 Pull/Push Factors

- **(Nominal) Interest rate**: I basically use the treasury bill rate (or deposit rate) of the IFS (International Financial Statistics) dataset (IMF) and complement the treasury bill yield of the Global Financial Database (https://globalfinancialdata.com/).
  - Brazil, Hungary, Israel, Mexico, South Africa, Thailand: I use the treasury bill rate at the IFS dataset as a nominal interest rate.
  - Chile, Colombia, Czech Rep., Indonesia, Korea Rep., Malaysia, Peru, Philippines, Russia, Turkey: I use the deposit rate of the IFS dataset which is close to the treasury bill rate since there is no data on treasury bill rate at the dataset.
  - China, India, Poland, Taiwan: I use the treasury bill yield at the Global Financial

dataset as a nominal interest rate since there is no appropriate data of interest rate at the IFS dataset.

- **Real interest rate**: I compute the real interest rate by subtracting the year-over-year growth rate of the consumer price index (CPI) from the (nominal) interest rate. CPIs are gathered from the IFS dataset (IMF) except for Taiwan. Taiwan's CPI is collected from Bloomberg.

- **Industrial production**: I use the not seasonally adjusted industrial production (US dollars) from the GEM (Global Economic Monitor) dataset (World Bank) and calculate the month-over-month growth rate[1] of industrial production.

- **Total reserve excluding gold**: I get the month-over-month growth rate[1] of total reserve excluding gold. The total reserve excluding gold (US dollars) is from the IFS dataset (IMF).

- **Exchange rate, Stock market index**: I use the month-over-month growth rate[1] of the exchange rates and stock market indices[2] each month. The monthly exchange rate and stock market index of each country are obtained from Bloomberg.

- **VIX**: I use the Chicago Board Options Exchange Volatility Index from Bloomberg.

[1] Month-over-month (MOM) growth rate is calculated by the log difference, i.e. $g_{X,t} = \log X_t - \log X_{t-1}$.

[2] The stock market indices I used are as follows: (Brazil) Bovespa, (Chile) S&P CLX IPSA, (China) Shanghai Composite, (Colombia) COLCAP, (Czech Rep.) PX, (Hungary) Budapest SE, (India) BSE Sensex 30, (Indonesia) Jakarta Stock Exchange Composite Index, (Israel) TA 35, (Korea Rep.) KOSPI, (Malaysia) FTSE Malaysia KLCI, (Mexico) S&P/BMV IPC, (Peru) S&P Lima General, (Philippines) PSEI Composite, (Poland) WIG 20, (Russia) MOEX Russia, (South Africa) South Africa Top 40, (Taiwan) Taiwan Weighted, (Thailand) SET Index, (Turkey) BIST 100

Appendix F

THE 17 INSTRUMENTS OF MACROPRUDENTIAL POLICY IN IMAPP DATABASE[1]

1. A requirement for banks to maintain a countercyclical capital buffer

2. Requirements for banks to maintain a capital conservation buffer, including the one established under Basel III

3. Capital requirements for banks, which include risk weights, systemic risk buffers, and minimum capital requirements

4. A limit on leverage of banks, calculated by dividing a measure of capital by the bank's non-risk weighted exposures (e.g., Basel III leverage ratio)

5. Loan loss provision requirements for macroprudential purposes, which include dynamic provisioning and sectoral provisions (e.g., housing loans)

6. Limits on growth or the volume of aggregate credit, the household-sector credit, or the corporate-sector credit, and penalties for high credit growth

7. Loan restrictions that include loan limits and prohibitions, which may be conditioned on loan characteristics (e.g., the maturity, the size, the LTV ratio, and the type of interest rate of loans), lender characteristics (e.g., mortgage banks), and other factors

8. Limits on foreign currency (FC) lending, and rules or recommendations on FC loans

9. Limits to the loan-to-value ratios, applied to residential and commercial mortgages but also applicable to other secured loans, such as for automobiles

10. Limits to the debt-service-to-income ratio and the loan-to-income ratio, which restrict the size of debt service payments or the size of a loan relative to income (e.g., household income, net operating income of the company)

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[1] https://www.elibrary-areaer.imf.org/macroprudential/pages/imappdatabase.aspx

11. Taxes and levies applied to specified transactions, assets, or liabilities, which include stamp duties, and capital gain taxes

12. Measures taken to mitigate systemic liquidity and funding risks, including minimum requirements for liquidity coverage ratios, liquid asset ratios, net stable funding ratios, core funding ratios, and external debt restrictions that do not distinguish currencies

13. Limits to the loan-to-deposit (LTD) ratio and penalties for high LTD ratios

14. Limits on net or gross open foreign exchange (FX) positions, limits on FX exposures and FX funding, and currency mismatch regulations

15. Reserve requirements (domestic or foreign currency) for macroprudential purposes

16. Measures taken to mitigate risks from global and domestic systemically important financial institutions (SIFIs), which include capital and liquidity surcharges

17. Macroprudential measures not captured in the above categories - e.g., stress testing, restriction on profit distribution, and structural measures (e.g., limits on exposures between financial institutions)

Appendix G

MACHINE LEARNING METHODS AND IMPLEMENTATION[1]

G.1 Random Forest

Random forests are a combination of de-correlated tree predictors and then averages them (Breiman (2001), Hastie et al. (2009)). It shows great performance on many problems, outperforming decision trees or bagging. They are popular as they provide reasonable predictions across a wide range of data with little configuration requirement.

Algorithm for Random Forest

---

1. For $b = 1$ to B:
   (a) Draw a bootstrap sample $\mathbf{Z}^*$ of size N from the training data.
   (b) Grow a random-forest tree T_b to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size n_{min} is reached.
      i. Select m variables at random from the p variables.
      ii. Pick the best variable/split-point among the m.
      iii. Split the node into two daughter nodes.
2. Output the ensemble of trees $\{T_b\}_1^B$.

To make a prediction at a new point x:

Regression: $\hat{f}_{rf}^B(x) = \frac{1}{B}\sum_{b=1}^B T_b(x)$.
Classification: Let $\hat{C}_b(x)$ be the class prediction of the bth random-forest tree. Then,
$\hat{C}_{rf}^B(x) = \text{majority vote } \{\hat{C}_b(x)\}_1^B$.

I use the *ranger* package in R to use random forests with tuning some parameters. I set the number of trees (*num.trees*) as 500, the maximal node size (*max.depth*) as 5, the number of variables to possibly split at in each node (*mtry*) as 9, and the minimal node size (*min.node.size*) as 2.

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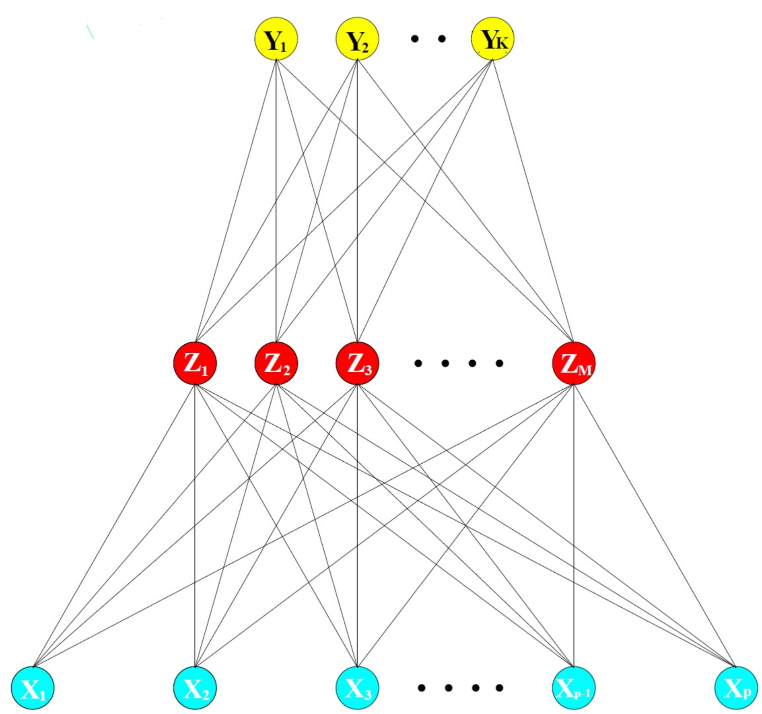
[1] This section is based on Hastie et al. (2009) and James et al. (2013).

G.2 Neural Network

A neural network is a multiple-stage regression or classification model, typically represented by a network diagram as in Figure G.1. All inputs (X) are transformed to the next layer by a weighted linear (or non-linear) combination. The weight is adjusted based on the strength of the signal as learning proceeds. Signals move from the input layer to the output layer and might traverse the layers multiple times. A neural network is very powerful and useful for many fields such as predictive modeling or adaptive control where they can be trained via a dataset.

Figure G.1: The example of neural network diagram with single hidden layer



I use the *nnet* package in R to use a neural network with tuning some parameters. I set the number of units in the hidden layer (*size*) as 2, the parameter for weight decay (*decay*) as 5e-4, and maximum number of iterations (*maxit*) as 300.

G.3 Boosted Tree

Boosted tree or Boosting combines the outputs of weak classifiers iteratively to generate the powerful classifier (Hastie et al. (2009)). They are added based on the pre-determined weight and the weight is updated each iteration based on the classifiers' accuracy. Boosting improves the predictions of a decision tree and is one of the most powerful learning methods.

Algorithm for Boosting (e.g. AdaBoost.M1)

---

1. Initialize the observation weights $w_i = 1/N$, $i = 1, 2, \ldots, N$.
2. For $m = 1$ to M:
   (a) Fit a classifier $G_m(x)$ to the training data using weights w_i.
   (b) Compute the error
   $$err_m = \frac{\sum_{i=1}^{N} w_i I(y_i \neq G_m(x_i))}{\sum_{i=1}^{N} w_i}$$
   (c) Compute $\alpha_m = \log((1 - err_m)/err_m)$.
   (d) Set $w_i \longleftarrow w_i \cdot \exp[\alpha_m \cdot I(y_i \neq G_m(x_i))]$, $i = 1, 2, \ldots, N$.
3. Output $G(x) = \text{sign}\Big[\sum_{m=1}^{M} \alpha_m G_m(x)\Big]$.

I use the *xgboost* package in R to use boosting with tuning some parameters. I set the step size of each boosting step (*eta*) as 0.1, and the max number of iterations (*nrounds*) as 35.

Appendix H

THE EFFECT OF MACROPRUDENTIAL POLICES ON AGGREGATE EQUITY FLOWS

H.1 Data

The data of monthly aggregate equity flows are gathered from the Institute of International Finance (IIF). I collect the aggregate flow data of 14 emerging countries – Brazil, Chile, Czech Republic, India, Indonesia, South Korea, Malaysia, Mexico, Philippines, Poland, South Africa, Taiwan, Thailand, and Turkey – from 2003 to 2018.

H.2 Model

I apply the same model used in Chapter 2 except for the dependent variable. The dependent variable in this Appendix is the degree of fluctuation of aggregate equity flows – the absolute value of the aggregate equity flow's change rate.

The aggregate equity flow of the IIF data represents the net flow so I obtain the change rate in aggregate equity flow by computing the ratio of net flow to nominal GDP for each country[1]. Since the volume of net flows varies across countries, I divide net flows by nominal GDP to compare between countries. And I calculate monthly nominal GDP by using cubic spline interpolation[2] because nominal GDP is given only quarterly. Finally, I multiply the ratio of net flow to nominal GDP by 100 to see the treatment effect apparently.

[1] This is different from how to get the change rate of equity flows for each investor in the EPFR dataset. I first calculate the total amount of mutual funds invested in each country for each investor and then compute the change rate of the total funds for each country and investor. This is because raw data from the EFPR dataset provides the amount of mutual funds allocated to each country

[2] Cubic spline interpolation is a method of constructing new points based on the set of known data points by using a cubic function, $y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + \epsilon_i$.

H.3 Result

Table H.1: The Effect of Macroprudential Policies on Aggregate Equity Flows (2003–2018)

Outcome	Linear	PLR model			
		(1)	(2)	(3)	(4)
Y_t	0.3913	0.1762	0.0173	-0.4121	0.2642
	(0.4265)	(0.4167)	(0.4621)	(0.4737)	(0.4324)
Y_{t+1}	-0.3698	-0.3434	-0.6268	-0.8760*	-0.5420
	(0.3129)	(0.3126)	(0.3248)	(0.3473)	(0.3628)
Outcome		IRM			
		(1)	(2)	(3)	(4)
Y_t		1.5780	0.1653	-0.4806	0.5617
		(2.0020)	(0.4974)	(0.6425)	(0.6834)
Y_{t+1}		-0.6885	-0.5315	-1.1103*	-0.3892
		(0.8710)	(0.3227)	(0.5637)	(0.3986)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors (HC2) in parentheses.
Notes: 1. Linear model in the second column is the simple linear regression model as follows:

$$Y_{c,t+h} = D_{c,t}\theta_0 + \boldsymbol{\beta X} + \xi_c + \xi_m + \epsilon_{ct}$$

where $Y_{c,t+h}$ is the absolute value of net aggregate equity flow (= |Net Equity Flows/GDP $\times$ 1000|) in the country c at time $t+h$ where $h \in \{0, 1\}$, $D_{c,t}$ is the treatments of tightening macroprudential policies in the country c at time t. θ_0 is the treatment effects of interests, correspondingly. X includes all the push and pull factors, and ξ_c and ξ_m represent the latent variables for countries, and months, respectively.
2. In the PLR model and IRM, g_0 and m_0 are specified as follows:
(1) Linear regression model, (2) Random forest, (3) Neural network, (4) Boosted tree

Table H.2: The Effect of Macroprudential Policies on Aggregate Equity Flows (After the GFC)

Outcome	Linear	PLR model (1)	(2)	(3)	(4)
Y_t	0.2834	0.1917	-0.2128	-0.7097	-0.1076
	(0.3382)	(0.3139)	(0.3687)	(0.3817)	(0.3557)
Y_{t+1}	0.1480	0.3396	-0.2338	-0.5921	-0.0649
	(0.3120)	(0.3126)	(0.3495)	(0.3557)	(0.3407)
Outcome		IRM (1)	(2)	(3)	(4)
Y_t		0.0567	-0.2234	-0.6151	0.0431
		(1.1089)	(0.4143)	(0.4630)	(0.5831)
Y_{t+1}		-0.6556	-0.3275	-0.7479	-0.4275
		(0.8608)	(0.3828)	(0.4454)	(0.4554)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors (HC2) in parentheses.
Notes: 1. Linear model in the second column is the simple linear regression model as follows:

$$Y_{c,t+h} = D_{c,t}\theta_0 + \boldsymbol{\beta X} + \xi_c + \xi_m + \epsilon_{ct}$$

where $Y_{c,t+h}$ is the absolute value of net aggregate equity flow (= |Net Equity Flows/GDP $\times$ 1000|) in the country c at time $t+h$ where $h \in \{0,1\}$, $D_{c,t}$ is the treatments of tightening macroprudential policies in the country c at time t. θ_0 is the treatment effects of interests, correspondingly. X includes all the push and pull factors, and ξ_c and ξ_m represent the latent variables for countries, and months, respectively.
2. In the PLR model and IRM, g_0 and m_0 are specified as follows:
(1) Linear regression model, (2) Random forest, (3) Neural network, (4) Boosted tree

Appendix I
MODEL PROOF

I.1 Strategy of Small Investors

The small investor's belief in equation (3.9) is derived from equation 3.5 as follows.

$$\begin{aligned}\mathbb{E}_i[\bar{s}] &= \psi_x \mathbb{E}_i\big[\textstyle\int_{[0,1)} x_j dj\big] + \psi_z z + \psi_l l = \psi_x \mathbb{E}_i[f] + \psi_z z + \psi_l l \\ &= \psi_x[\alpha_x x_j + \alpha_z z] + \psi_z z + \psi_l l. \end{aligned} \tag{I.1}$$

Recall equation (3.10). Then, we obtain

$$\begin{aligned} s_j^* &= (1-\theta)[\alpha_x x_j + \alpha_z z] + \theta\big\{\lambda l + (1-\lambda)\big\{\psi_x[\alpha_x x_j + \alpha_z z] + \psi_z z + \psi_l l\big\} \\ &= \big[(1-\theta)\alpha_x + \theta(1-\lambda)\psi_x\alpha_x\big]x_j + \big[(1-\theta)\alpha_z + \theta(1-\lambda)(\psi_x\alpha_z + \psi_z)\big]z + \big[\theta\lambda + \theta(1-\lambda)\psi_l\big]l, \end{aligned} \tag{I.2}$$

which yields the following equations.

$$\psi_x = [(1-\theta) + \theta(1-\lambda)\psi_x]\alpha_x, \tag{I.3}$$

$$\psi_z = \left[(1-\theta) + \theta(1-\lambda)\left(\psi_x + \frac{\psi_z}{\alpha_z}\right)\right]\alpha_z. \tag{I.4}$$

$$\psi_l = \theta[\lambda + (1-\lambda)\psi_l]. \tag{I.5}$$

From equation (I.3), we obtain equation (3.11) directly. Equation (3.13) is also directly from equation (I.5). Putting ψ_x into equation (I.4), we obtain equation (3.12).

$$\begin{aligned}\psi_z &= \left[(1-\theta)+\theta(1-\lambda)\left(\psi_x+\frac{\psi_z}{\alpha_z}\right)\right]\alpha_z = \left[\frac{(1-\theta)+\theta(1-\lambda)\psi_x}{1-\theta(1-\lambda)}\right]\alpha_z \\ &= \left[\frac{(1-\theta)+\frac{\theta(1-\lambda)(1-\theta)\alpha_x}{1-\theta(1-\lambda)\alpha_x}}{1-\theta(1-\lambda)}\right]\alpha_z = \left\{\frac{1-\theta}{[1-\theta(1-\lambda)][1-\theta(1-\lambda)\alpha_x]}\right\}\alpha_z \end{aligned} \tag{I.6}$$

To prove Lemma 1, derive equation (3.14). Recall equations (I.3) and (I.4).

$$\psi_x = \big[(1-\theta)+\theta(1-\lambda)\psi_x\big]\alpha_x \tag{I.7}$$

$$\psi_z = \left[(1-\theta)+\theta(1-\lambda)\left(\psi_x+\frac{\psi_z}{\alpha_z}\right)\right]\alpha_z \tag{I.8}$$

Then, $\psi_x/\alpha_x - \psi_z/\alpha_z$ is

$$\frac{\psi_x}{\alpha_x}-\frac{\psi_z}{\alpha_z} = -\theta(1-\lambda)\frac{\psi_z}{\alpha_z} \tag{I.9}$$

$$\frac{\psi_x}{\psi_z} = [1-\theta(1-\lambda)]\frac{\alpha_x}{\alpha_z}, \tag{I.10}$$

Thus, we obtain the ratio:

$$\frac{\psi_x}{\psi_z} = [1-\theta(1-\lambda)]\frac{\alpha_x}{\alpha_z}, \tag{I.11}$$

which should not be larger than α_x/α_z because of $\theta(1-\lambda) \in [0,1]$. Take a logarithmic function on both sides, we get the results.

$$\frac{\partial \ln(\psi_x/\psi_z)}{\partial \ln(\alpha_x/\alpha_z)} = 1. \tag{I.12}$$

Proposition 1 is from the partial derivatives of equations (3.11), (3.12), and (3.13) as follows.

$$\frac{\partial \psi_x}{\partial \lambda} = \frac{\partial}{\partial \lambda}\left[\frac{(1-\theta)\alpha_x}{1-\theta(1-\lambda)\alpha_x}\right] = \frac{-\theta(1-\theta)\alpha_x^2}{[1-\theta(1-\lambda)\alpha_x]^2} < 0 \tag{I.13}$$

$$\begin{aligned}\frac{\partial \psi_z}{\partial \lambda} &= \frac{\partial}{\partial \lambda}\left\{\frac{(1-\theta)\alpha_z}{[1-\theta(1-\lambda)][1-\theta(1-\lambda)\alpha_x]}\right\} \\ &= \left\{\frac{-(1-\theta)\theta\alpha_z}{[1-\theta(1-\lambda)]^2[1-\theta(1-\lambda)\alpha_x]}\right\} + \left\{\frac{-(1-\theta)\theta\alpha_x\alpha_z}{[1-\theta(1-\lambda)][1-\theta(1-\lambda)\alpha_x]^2}\right\} < 0 \end{aligned}\tag{I.14}$$

$$\frac{\partial \psi_l}{\partial \lambda} = \frac{\partial}{\partial \lambda}\left[\frac{\lambda\theta}{1-\theta(1-\lambda)}\right] = \frac{(1-\theta)\theta}{[1-\theta(1-\lambda)]^2} > 0, \tag{I.15}$$

where $\theta \in (0,1)$.

To prove Corollary 1, combine equations (3.13) and (3.12).

$$\begin{aligned}\frac{\psi_l}{\psi_z} &= \left\{\frac{\lambda\theta}{1-\theta(1-\lambda)}\right\}\left\{\frac{[1-\theta(1-\lambda)][1-\theta(1-\lambda)\alpha_x]}{(1-\theta)\alpha_z}\right\} \\ &= \frac{\lambda\theta[1-\theta(1-\lambda)\alpha_x]}{(1-\theta)\alpha_z},\end{aligned}\tag{I.16}$$

which is increasing function of λ for $\theta \in (0,1)$ because both $\lambda\theta$ and $1-\theta(1-\lambda)\alpha_x$ increase with λ. Taking a logarithmic function in both sides of the above equations, we have

$$\ln\frac{\psi_l}{\psi_z} = \ln\lambda + \ln\theta + \ln[1-\theta(1-\lambda)\alpha_x] - \ln(1-\theta) - \ln\alpha_z. \tag{I.17}$$

The partial derivative with respect to λ is

$$\frac{\partial \ln \psi_l/\psi_z}{\partial \ln\lambda} = 1 + \frac{\partial \ln\left[1-\theta(1-e^{\ln\lambda})\alpha_x\right]}{\partial \ln\lambda} = 1 + \frac{\theta\lambda\alpha_x}{1-\theta(1-\lambda)\alpha_x} \tag{I.18}$$

I.2 Strategy of Large Investor

Since $\bar{s}(l) = \psi_x \int_{[0,1)} x_j dj + \psi_z z + \psi_l l$ and $\int_{[0,1)} x_j dj = f$, the large investor's belief on the average small investor's action $\bar{s}$ given the information z is

$$\begin{aligned}\mathbb{E}_1[\bar{s}] &= \psi_x \mathbb{E}_1[f] + \psi_z z + \psi_l l = (\psi_x \beta + \psi_z) z + \psi_l l \\ &= \left[\frac{1-\theta}{1-\theta(1-\lambda)}\right] \beta z + \psi_l l = (1-\psi_l)\beta z + \psi_l l. \end{aligned} \tag{I.19}$$

To derive the large investor's optimal strategy, we plug $\bar{s}(l) = \psi_x \int_{[0,1)} x_j dj + \psi_z z + \psi_l l$ and $\int_{[0,1)} x_j dj = f$ into equation (3.17).

$$\begin{aligned}\pi_1(l; f, \bar{s}(l)) &= -\frac{1}{2}\mathbb{E}_1\left[(1-\theta)(l-f)^2 + \theta[l - \lambda l - (1-\lambda)\bar{s}(l)]^2\right] \\ &= -\frac{1}{2}\mathbb{E}_1\left[(1-\theta)(l-f)^2 + \theta(1-\lambda)^2(1-\psi_l)^2[l - (1-\lambda)(\psi_x f + \psi_z z)]^2\right] \end{aligned} \tag{I.20}$$

Then, the first order condition is

$$\begin{aligned} 0 &= -\mathbb{E}_1\left[(1-\theta)(l-f) + \theta(1-\lambda)^2(1-\psi_l)^2[l - (1-\lambda)(\psi_x f + \psi_z z)]\right] \\ &= -\left[(1-\theta) + \theta(1-\lambda)^2(1-\psi_l)^2\right] l + (1-\theta)\mathbb{E}_1[f] + \theta(1-\lambda)^2(1-\psi_l)^2\{\psi_x \mathbb{E}_1[f] + \psi_z z\} \\ \therefore \quad l &= \frac{(1-\theta)\mathbb{E}_1[f] + \theta(1-\lambda)^2(1-\psi_l)^2\{\psi_x \mathbb{E}_1[f] + \psi_z z\}}{(1-\theta) + \theta(1-\lambda)^2(1-\psi_l)^2} \end{aligned} \tag{I.21}$$

To express the above optimal decision rule in terms of the response to information of large investors, we use the following relationship.

$$\psi_x + \frac{\psi_z z}{\mathbb{E}_1[f]} = \psi_x + \frac{\psi_z}{\beta} = 1 - \frac{\theta\lambda}{1-\theta(1-\lambda)} \tag{I.22}$$

where $\alpha_z/\beta = (\sigma_f^2 + \sigma_z^2)/(\sigma_f^2 + \sigma_x^2 + \sigma_z^2) = 1 - \alpha_x$.

Equation (I.22) can be obtained as follows.

$$\begin{aligned}\psi_x + \frac{\psi_z}{\beta} &= \psi_x\left[1 + \left(\frac{\psi_z}{\psi_x}\right)\frac{1}{\beta}\right] = \psi_x\left[1 + \frac{(1-\alpha_x)/\alpha_x}{1-\theta(1-\lambda)}\right] = \frac{\psi_x}{\alpha_x}\left[\frac{1-\theta(1-\lambda)\alpha_x}{1-\theta(1-\lambda)}\right]\\ &= \left[\frac{1-\theta}{1-\theta(1-\lambda)\alpha_x}\right]\left[\frac{1-\theta(1-\lambda)\alpha_x}{1-\theta(1-\lambda)}\right] = \frac{1-\theta}{1-\theta(1-\lambda)} = 1 - \frac{\theta\lambda}{1-\theta(1-\lambda)}\end{aligned}$$

Plugging equations (3.13) and (I.19) into equation (I.21), we obtain the first order condition (3.18) as follows.

$$\begin{aligned} l &= \left[1 - \frac{\theta(1-\lambda)^2(1-\psi_l)^2(1-\psi_x-\psi_z/\beta)}{(1-\theta)+\theta(1-\lambda)^2(1-\psi_l)^2}\right]\beta z\\ &= \left[1 - \frac{\theta(1-\lambda)^2(1-\psi_l)^2\psi_l}{(1-\theta)+\theta(1-\lambda)^2(1-\psi_l)^2}\right]\beta z \end{aligned} \tag{I.23}$$

where we replace $1-\psi_x-\psi_z/\beta$ equation (I.22).