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Global volatility and firm-level capital flows☆

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ABSTRACT

We study the impact of global volatility on the equity portfolio flows of institutional investors worldwide. Aggregate equity allocations of institutional investors decrease during periods of high volatility, both in developed and, even more strongly, in emerging markets. Our granular portfolio-level data allows us to uncover disaggregated investor responses that are an order of magnitude larger than aggregate estimates, and are dominated by discretionary (investor-driven) component of flows. We further show that periods of high volatility are associated with portfolio rebalancing by institutional investors from small-cap to large-cap stocks. Finally, institutional flows have significant impact on future firm stability, measured by their volatility and liquidity. Our findings are consistent with the economic mechanism in which investors with heterogeneous information capacity are learning about assets with different information rents.

1. Introduction

Portfolio flows are a significant determinant of stability in global financial markets. This observation becomes particularly apparent during periods of high volatility and global market stress, when substantial capital outflows can escalate into panics, leading to a depletion of wealth, heightened stock price volatility, and reduced economic output (Allen and Gale, 1998). Empirical research has demonstrated that sophisticated investors tend to retrench their capital significantly during times of global stress (Forbes and Warnock, 2012; Broner et al., 2013). This line of research, however, relies on aggregate data and thus faces limitations when it comes to identifying the underlying economic forces of flow dynamics. First, it cannot attribute the flow of aggregate capital to specific investor and firm characteristics, especially if the composition of assets and investors changes over time. Second, it cannot distinguish between factors that are at the discretion of portfolio managers and those that depend on demand pressure from such managers' external clients or regulatory and investor constraints. Finally, it cannot differentiate between explanations based on portfolio-wide fire sales and those based on stock-investor-specific information asymmetries.

To address these limitations, we employ detailed micro-level data on institutional investors' stock portfolios, covering nearly 30,000 firms from 41 economies over the 2000–2020 period.[1] With these data, we study individual micro-elasticities of institutional flows with respect to aggregate market stress. We show that institutional investors tend to retrench from holding stocks in times of stress. However, this retrenchment is not uniform but is instead heterogeneous across asset characteristics, such as size and idiosyncratic volatility, as well as across the location of the assets. We show that this behavior is consistent with the predictions of an equilibrium model in which investors with different information capacity learn about assets that are heterogenous in these two dimensions. To better capture our mechanism empirically, we isolate the *discretionary* component of portfolio flows, by controlling for the variation due to time-varying aggregate portfolio effects and time-invariant selection of investors to stocks. We find that the discretionary component is much more sensitive

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[1] Other papers showing the importance of detailed micro-level investment data include Coppola et al. (2021), Maggiori et al. (2020), which study international investment positions, and Camanho et al. (2018) whose focus is on the interaction of exchange rates and portfolio rebalancing.

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to aggregate shocks than the part of the flow driven by external investor inflows/redemptions or portfolio mandates. Finally, we show that the institutional flows have positive effect on financial stability of individual assets. Overall, our research is among the first to leverage high-granularity data to establish the determinants of global portfolio flows, their influence on financial market stability, and more broadly, the propagation of shocks in the economy.

To establish our quantitative benchmark for the discretionary investor-level choices, we begin with the analysis at the *firm level*. Specifically, we relate percentage changes in firm-level equity shares to levels of global volatility, which we measure as a within-quarter volatility of daily stock returns in the MSCI ACWI global index. We find that institutional investors, in aggregate, tend to reduce their average stock positions in times of high volatility. Given that the finding comes from the model estimated using firm-level data, we are able to absorb any variation specific to country-level controls, such as levels and volatility of exchange rates, interest rates, and volatility of local market returns, thereby shifting our focus from macro-level to firm-investor-level drivers. Further, including various time-varying firm characteristics allows us to rule out explanations related to changing firm-specific risk exposures. Finally, by employing firm-fixed effects, we can absorb any variation in flows resulting from time-invariant firm-level unobservables, such as stable aggregate preferences for specific assets, which are less reflective of the active response of investors to volatility changes. We further find that the estimated effects are economically strong for firms in both developed and emerging markets, even though the magnitude of the results is relatively smaller in developed markets. The results extend a common view on the role of market stress for portfolio flows, such as the theory of sudden stops, beyond emerging markets.

Although our firm-level evidence provides a more comprehensive understanding of the flow dynamics compared to market-level analyses, it still does not account for inherent differences among investors and their potential heterogeneous selection into individual assets. Consequently, our results are consistent with a number of economic explanations, such as an increase in risk aversion of institutional investors, portfolio-level differences in investor clienteles, as well as explanations based on permanent skills or style preferences of institutional investors for certain assets. Moreover, the firm-level results presume a stable investor base composition under different market conditions. However, it is possible that investors with more elastic portfolio responses are relatively more likely to participate in the market during high-volatility periods, which could lead the firm-level results to merely reflect this composition effect. To assess the relative importance of all such channels, we turn to *investor-firm-level* data to estimate the flow elasticities.

The results from these more granular tests significantly amplify the estimated effect of global volatility on investor-firm-level outflows. To assess the underlying sources of variation in the data, we saturate our specification with firm-level and investor-level controls. In the first set of tests, in which we replace firm-level with firm-investor-level variation, we find that institutional flows decline by more than double the effect for firm-level aggregates as a consequence of an increase in global volatility. This result implies that the composition of investors captured in the firm-level data is likely skewed towards those with lower sensitivity of portfolios to changing global volatility. The investor-firm-level effect grows by almost 50% once we account for the stable selection of firms into individual portfolios using firm-investor fixed effects. Consequently, the selection of institutional investors to specific stocks plays an important role in driving the economic magnitude of portfolio flows—a result that could not have been anticipated from tests using aggregate or firm-level data alone. Concretely, by moving from evidence solely based on firm-level data to investor-firm-level data, we observe an increase in flow sensitivity by a factor of five for the sample of firms in developed markets sample and a factor of six for the sample in emerging markets.

We further propose an economic mechanism behind our results, which exploits investors' heterogeneity in information processing capacity in a model of endogenous learning about assets with different information rents. Our model features investor and firm-level heterogeneity, which are the primary characteristics of our data, and additionally incorporates a natural aspect of investing in financial markets under imperfect information by allowing investors to optimize their learning about asset payoffs.[2] In the model, we consider two investor types, institutional and retail, who differ in size and risk aversion, as well as their ability to process information about asset payoffs. Building on past empirical evidence (Bena et al., 2017; Kacperczyk et al., 2021), we posit and empirically verify that institutional investors are more informed than their retail counterparts. Investors make learning and trading decisions about a set of risky assets that are heterogeneous in their size and payoff volatility.[3] Thanks to this rich heterogeneity, our model can be used to differentiate between explanations driven by risk aversion shocks implying market-wide outflows, relative to explanations premised on investors' differential learning about individual assets.

Specifically, we model the global volatility shock as a shock to the aggregate volatility of payoffs, combined with a shock to institutional risk aversion. We demonstrate that in response to such shock, institutional investors, relative to retail investors, tend to retrench and rebalance their portfolios away from small stocks towards large stocks. Additionally, we show that this cross-sectional pattern critically depends on the endogenous responses of learning to the shock and disappears in an exogenous learning environment. Intuitively, learning gains in the model are high for large stocks (which have prices less sensitive to holdings and learning) and volatile stocks (which have high unconditional risk premia). Both these factors increase in times of high aggregate volatility, thus driving the cross-sectional relocation of learning and trading. We further apply the model to a setting in which informational advantage of institutional investors depends on their investing environment. We posit and verify that such informational gap is likely wider in emerging markets than in developed markets. Since institutional investors in emerging markets are more sophisticated relative to retail investors, their learning has a comparatively more significant effect on their portfolio holdings than in developed markets. The model exhibits a similar mechanism for high versus low-volatility stocks, with investors rebalancing towards high-volatility stocks. However, the size effect dominates quantitatively and thus is the main focus of our analysis. As a final result, we show that the model predicts a robust positive cross-sectional relationship between institutional ownership and stock turnover.

Next, we test these theoretical results in our data. To this end, we study investors' portfolio responses to global volatility shocks at the level of individual assets. Our findings reveal that during periods of high global volatility, institutional investors, both domestic and foreign, tend to withdraw their capital from small-cap stocks significantly more than from large-cap stocks. This effect holds while controlling for a range of firm characteristics, as well as firm and investor-fixed effects. We also observe that this effect is more pronounced in a sample of firms from emerging markets compared to those from developed markets.

[2] Our model is based on the framework of Kacperczyk et al. (2019), but is closely related to a number of contributions that use a noisy rational expectations framework to study the impact of investor heterogeneity, such as Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010), or Kacperczyk et al. (2016).

[3] Our assumptions contrast with other theoretical models of flows, such as Albuquerque et al. (2007, 2009), or Brennan and Cao (1997), who study trading and learning decisions in a model with exogenous information, multiple countries and a single asset per country, or Kodres and Pritsker (2002), who focus on the effects of cross-country correlations in returns. Within the context of our analysis, our model with multiple assets provides a better map to the data.

Furthermore, we find that in response to global stress, institutional investors rebalance their portfolios towards high-volatility assets, even after controlling for size and other factors. These predictions are consistent with the proposed theoretical mechanism and do not support explanations that solely rely on indiscriminate liquidation of stocks driven by home bias or differences in risk aversion, as these explanations would not imply variations in retrenchment across assets. In general, our findings uncover an alternative, information-driven flight-to-quality effect, different than are typically documented for aggregate assets.

In the subsequent series of tests, we connect the investor-firm-time variation to stock ownership of foreign and domestic institutions. These tests allow us to gauge the relative significance of *discretionary* determinants of flows, such as time-varying managerial stock-picking skills vs. *non-discretionary* factors, such as portfolio mandates or time-varying portfolio redemptions. The latter poses a particularly significant empirical challenge in tests that rely on aggregate data. In a sample of all stocks, we find that both domestic and foreign institutional investors exhibit a tendency to reduce their equity flows to stocks with smaller size and lower volatility. Remarkably, when we restrict our sample to firms in emerging markets, we find that foreign institutions tend to reduce their equity flows to smaller stocks more than domestic institutions do. This result is consistent with the hypothesis that in such markets foreign investors are relatively more informed and thus are more sensitive to global uncertainty shocks.

We further assess the boundaries of the cross-asset reallocation results in light of the apparent heterogeneity of institutional investors. First, we study flow elasticities conditional on the asset domicile. The portfolio sensitivities are larger for firms in Europe and Asia. Second, we show that the rebalancing effect towards large stocks is stronger for investors who have more information capacity, such as investors whose assets under management are larger, who are actively managing their portfolios, and those whose performance in the previous year is better. Third, we show that such informed investors are more sensitive to global stress in emerging markets than in developed markets. Finally, turning to the extensive margin adjustment, we show that in periods of high global volatility, more sophisticated investors tend to enter into positions in large stocks and exit from small stocks. All these results are consistent with our postulated information-based mechanism.

We subsequently examine the robustness of our economic mechanism to potential endogeneity concerns. We first note that our use of high-granularity data, combined with a high-dimensional set of fixed effects, makes it unlikely that our results can be attributed to an unspecified omitted variable. In particular, such a variable would have to vary at the institutional-firm-time level and not purely at firm-time, investor-time, or investor-firm level, since these dimensions of variability are already absorbed by our fixed effects. Nonetheless, to buttress our identification, we conduct two additional empirical analyses. In the first one, we assess the sensitivity of our findings to different measures of global uncertainty. We consider four alternative measures of global stress, including indicators for the Global Financial Crisis and the COVID crisis, Financial Uncertainty Index, VIX, and lagged global volatility. The results based on the four different measures of uncertainty paint a very similar picture as those we report in our baseline regressions, which makes it unlikely that the results are subject to a potential reverse causality concern or are spuriously driven by a specific choice of our volatility measure. It is noteworthy that the specific impact of crisis episodes on flows is more pronounced in the sample of firms in emerging markets, consistent with the prevalent macro view of global stress affecting emerging economies more substantially (Calvo et al., 1996; Rothenberg and Warnock, 2011).

In the second set of robustness results, we instrument global volatility using two popular variables. Our first instrument is based on the Granular Instrumental Variable (GIV) approach of Gabaix and Koijen (2024), which argues that idiosyncratic components of large stocks can have aggregate implications. In this spirit, our instrument is the idiosyncratic stock-level turnover of large stocks. Our second instrument is the U.S. monetary policy "news" shock (MPS) of Nakamura and Steinsson (2018). Both instruments have a statistically significant positive effect on global volatility, thus satisfying the relevance condition. They also feature plausible exogeneity, thus satisfying the exclusion restriction. We apply each of the instruments to our cross-sectional regressions. The estimated coefficients are similar across both instruments and only slightly elevated relative to the baseline panel regression estimates, thus suggesting that our results are not severely affected by endogeneity of global volatility measure.

In the final section of the paper, we explore the implications of the flow dynamics for financial stability, which we assess using firm-level stock return volatility and stock turnover. Our findings indicate that *outflows* from institutional investors are linked to future increases in firm volatility and decreases in firm turnover, implying that institutional flows contribute to market stabilization. While the effect on volatility is observed in both developed and emerging markets, the impact on turnover primarily manifests itself in developed markets. Considering that foreign investors, on average, withdraw less from large stocks during times of stress, these results suggest that such firms may indeed benefit from the presence of foreign investors.

Related literature. Our paper contributes to a body of empirical literature relating international capital flows to aggregate shocks. Broner et al. (2013) use data on flows by foreign and domestic agents, disaggregated into broad direct, portfolio, and other categories. They show that foreign flows of all types are pro-cyclical and they go down in periods of crises. Avdjiev et al. (2018) study debt flows by sector (public, bank, corporate) in response to global shocks, finding large responses of international bank flows to the shock. Forbes and Warnock (2012) find that global risk is strongly associated with extreme international capital flows events, and that domestic macroeconomic factors play a lesser role. Fratzscher (2012) studies capital flows during the global financial crisis at the fund level, finding significant relocation across countries. Chari et al. (2022) study the effects of global shocks on the tails of the distribution of country-level flows to emerging markets.

Within the flow literature, some studies focus on the distinction between discretionary and outside flows. Shek et al. (2018) show that discretionary sales by bond fund managers are a significant part of total sales, in addition to sales driven by redemptions. Raddatz and Schmukler (2012) also document that a part of the cross-country relocation in response to aggregate shocks is due to fund managers' decisions. In our analysis, we are able to capture the discretionary response of managers' equity allocations to shocks by controlling for the time-varying fund effects. To our knowledge, we are the first to study responses of international portfolio flows at the firm-investor level. The granularity of our data also allows us to capture the average behavior of domestic and foreign investors, as well as the stock-specific responses of each investor type. We show that in the disaggregated data, the estimated sensitivities to global shocks increase by almost an order of magnitude. Crucially, the new cross-sectional dimension allows us to generate additional testable predictions to distinguish between different economic mechanisms of flows dynamics.

The literature utilizing cross-sectional variation in the flow data is fairly sparse. Two notable exceptions include Hau and Lai (2017) and Coppola et al. (2021). Hau and Lai (2017) study the aggregate behavior of distressed global funds during the global financial crisis. They find a shift in such funds' portfolio positions towards liquid stocks. Their study is based on the data aggregated at the firm level; thus they abstract from cross-investor variation, which is the central aspect of our design. Notably, our empirical findings are consistent with theirs to the extent that large stocks are more liquid. Coppola et al. (2021) show a significant degree of financing of global firms through foreign subsidiaries. Our analysis is independent of such activity, as our focus is on the impact of global shocks on local equity markets and its implications for local market stability.

Our paper provides evidence on individual investor responses that can help distinguish between economic mechanisms in the theoretical literature on international portfolio investment flows. Coeurdacier and Rey (2013) give a comprehensive discussion of determinants of portfolios' home bias in a variety of theoretical setups, including ones based on information frictions, first explored in Van Nieuwerburgh and Veldkamp (2009). Brennan and Cao (1997), Albuquerque et al. (2007, 2009) consider models with exogenous signals in which investors are heterogeneous in the quality of their signals. Albuquerque et al. (2009) feature foreign investors that have superior information about global shocks and show such model can generate a positive flow-return relationship for U.S. investors. Caballero and Simsek (2020) consider the implication of foreign investor fickleness and retrenchment in response to local liquidity shocks.

From a different perspective, our paper connects to the growing literature on demand systems of asset managers and the price elasticity of their portfolio choices. An influential paper by Gabaix and Koijen (2021) shows that institutional flows in equity markets exhibit low price elasticity. They argue that institutional constraints may be the driving force. Our results are consistent with these findings, but our main focus is on measuring the response of discretionary flows across investor types and assets, rather than on estimating elasticities of aggregate flows. The distinct advantage of our study is that we can directly quantify the importance of institutional constraints for investor-level flows by exploiting the investor-time variation in our data. We find that controlling for investor-time fixed effects, the estimated response of flows increases by an order of magnitude, thus confirming the importance of fund-level constraints for price elasticities.

Finally, our paper also relates to studies of macroeconomic uncertainty. Notable recent examples of papers pointing out the importance of financial market uncertainty and realized volatility in financial markets for macroeconomic outcomes in the U.S. include Berger et al. (2020) and Ludvigson et al. (2021). Since our outcome of interest are global portfolio flows, our shock is global realized equity portfolio volatility. However, our measure of global volatility is highly correlated with country-level volatilities, index of option-implied volatility VIX, and the measure of financial uncertainty derived by Ludvigson et al. (2021).[4] Finally, we provide evidence on the relationship between institutional flows and firm-level volatility and liquidity, thus contributing to the broader literature studying the interaction of institutional ownership and asset returns, such as Schwert (1989), Gompers and Metrick (2001), Campbell et al. (2001), or theoretically Gabaix et al. (2006).

The rest of the paper is organized as follows. In Section 2, we describe the data. Section 3 presents the baseline results relating capital flows and global volatility using different dimensions of data aggregation. In Section 4, we propose a general equilibrium information-based framework as a mechanism to explain our results. We further use predictions of the model to confirm the robustness of our model. Finally, we use different empirical strategies to buttress identification of the estimated coefficients. In Section 5, we show empirical results on the link between institutional flows and financial stability. Section 6 concludes.

2. Data

Our primary data set is a panel derived from the integration of multiple databases. We obtain global institutional holdings data from FactSet, and firm-level international stock market and accounting data from Thomson/Refinitiv Datastream. FactSet provides holdings information for a diverse array of institutions, including mutual funds, hedge funds, bank trusts, pension funds, insurance companies, and sovereign wealth funds. Our data, updated quarterly, covers the period between 2000 and 2020. We retain firms with a minimum of three years of complete data and markets with at least 10 firms per quarter. Our focus is on ordinary shares, thereby excluding preferred shares, American Depositary Receipts (ADR), and Global Depositary Receipts (GDR) from our sample. In cases of dual listings, only primary listings are retained. The final dataset comprises 30,230 distinct firms and 13,145 portfolios across 41 different economies. In Appendix B, we present the distribution of our sample coverage relative to the IMF Coordinated Portfolio Investment Survey (CPIS) data for individual countries in the year 2020. On average, our sample covers a significant portion of equity values reported in the IMF, approximately 60%[5] Notably, the IMF data covers all types of equity, whereas we concentrate on primary listings of ordinary shares, and hence this number understates the true coverage of our data for equity flows.

Institutional ownership is assessed at both the firm and investor-firm levels. At the investor-firm level, institutional ownership, denoted as $IO_{i,j,t}$, represents the proportion of firm i's shares held by institution j at time t. An indicator variable, FOR, is assigned a value of one when an institution and a firm in its portfolio are based in different countries; otherwise, it is set to zero. In our empirical analyses, equity flows are defined as the log change in institutional ownership, represented by $\Delta Log(IO)$. Firm-level control variables include the natural logarithm of firm size ($Logsize$); quarterly return volatility (Vol), calculated using daily returns within a quarter; book-to-market ratio (BM); $Leverage$, which is the book debt divided by total assets; $Turnover$, determined as the trading volume divided by the total outstanding shares; and Profitability ($PRratio$), defined as the ratio of gross profits to total assets. In addition to firm characteristics, we employ institution-level control variables. Institutional assets under management ($Log(InsAUM)$) represent the sum of values of all stock holdings at the most recent quarter end. Institution return ($InsRet$) is gauged as the value-weighted portfolio return of stocks held at the most recent quarter end. All firm and institution-level control variables are demeaned in the regression analysis. To mitigate the impact of outliers, we winsorize all variables at the 1% level.

We source macro-level variables from Thomson/Refinitiv Datastream. Our primary independent variable is global stock market volatility ($Gvol$), which is based on the return of the MSCI ACWI index. This index is among the most popular and comprehensive global indices. $Gvol$ measures the end-of-quarter daily volatility of realized returns, an indicator that has been shown to influence macroeconomic activity in the U.S. context.[6] Local stock market volatility ($Lvol$) is determined by the volatility based on daily returns of country-specific stock market indices. ΔIR represents the quarterly change in the three-month interest rate. Foreign exchange rate return ($FXret$) corresponds to the quarterly change in the exchange rate relative to the US dollar. Foreign exchange rate volatility ($FXvol$) is calculated using the volatility based on daily exchange rate fluctuations. For US firms, both $FXret$ and $FXvol$ are set to zero.

We present summary statistics in Table 1, and Tables C.1 and C.2 of Appendix C. On average, firms in developed markets exhibit higher institutional ownership than those in emerging markets. U.S. firms have the highest average ownership at 60.84%, with 55.34% attributable to domestic institutional investors and 5.5% to foreign institutional investors. Firms in emerging markets display a higher

4 In Appendix A, we report correlations between our measure of global volatility, individual countries' volatilities, as well as measures used in Ludvigson et al. (2021), Baker et al. (2016), the world uncertainty index of Ahir et al. (2022), and global policy uncertainty index of Davis (2016).

5 FactSet has been employed for analyses of institutional investors in studies such as Ferreira and Matos (2008), Kacperczyk et al. (2021), Koijen et al. (2023).

6 See Berger et al. (2020) and references therein. Our measure correlates with country-level indices in our dataset, which we control for, and hence is not a strictly US-centric measure. In Appendix A, we report correlations of $Gvol$ with local market volatilities ($Lvol$), as well as other measures of volatility and economic uncertainty used in the literature.

Table 1
Summary statistics: Variables.
The sample period is 2000–2020 and firms are observed at a quarterly frequency. This table reports the mean, standard deviation, median, 10th, and 90th percentiles for institutional ownership, market, and accounting variables. Panel A reports statistics on institution-firm level, and Panel B reports statistics on firm level. In Panel A, FOR is an indicator variable that equals to one if the institution and firm are from different economies, $Gvol$ is quarterly volatility based on daily return of the MSCI ACWI index. Firm variables include the natural logarithm of firm market capitalization ($Logsize$), stock volatility, turnover ratio, leverage, book-to-market (BM), and profitability ($PRratio$). Institutional-investor variables include the natural logarithm of institution investor's total asset under management ($Log(InsAUM)$) and institution investor's return ($InsRet$). Economy-wide variables include local market stock return volatility ($Lvol$), change of three-month interest rate (ΔIR), currency return ($FXRet$), and currency volatility ($FXvol$).

Variables	Mean	STD	Q10	Median	Q90
Panel A: Investor - Firm Level					
$\Delta Log(IO)$	0.147	3.458	−1.106	0.000	2.169
FOR	0.463	0.500	0.000	0.000	1.000
$Gvol$	0.009	0.005	0.005	0.007	0.014
$Logsize$	8.388	1.830	5.774	8.420	10.943
Vol	0.028	0.038	0.011	0.019	0.040
$Turnover$	0.447	0.410	0.088	0.331	0.933
$Leverage$	0.232	0.183	0.002	0.213	0.477
BM	0.548	0.444	0.126	0.444	1.097
$PRratio$	0.319	0.238	0.065	0.266	0.631
$Log(InsAUM)$	8.117	2.487	4.774	8.278	11.189
$InsRet$	0.045	0.093	−0.077	0.150	0.150
$Lvol$	0.012	0.007	0.006	0.010	0.010
ΔIR	−0.039	0.377	−0.317	0.000	−0.317
$FXRet(\%)$	0.000	0.029	−0.027	0.000	0.029
$FXvol$	0.002	0.003	0.000	0.000	0.006
Panel B: Firm Level					
$\Delta Log(IO)$	0.019	0.276	−0.168	0.000	0.217
$Gvol$	0.009	0.005	0.005	0.007	0.014

Table 2
Global volatility and capital flows: Firm-level heterogeneity.
This table presents the firm-level regression results for the relation between global volatility and institutional ownership changes based on a firm-quarter sample observed between 2000 and 2020. We report the results for the full sample, as well as developed and emerging markets sub-samples. The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variable is global volatility ($Gvol$). Control variables include firm characteristics ($Logsize$, Vol, $Turnover$, $Leverage$, BM, and $PRratio$) and macro variables ($Lvol$, ΔIR, $FXRet$, and $FXvol$). Section 2 provides detailed definitions of these variables. All regression models include firm-fixed effects. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ALL				Developed	Emerging
	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta Log(IO)_{i,t}$					
$Gvol_t$	−2.692***	−3.609***	−3.686***	−3.713***	−3.442***	−4.652***
	(0.378)	(0.523)	(0.567)	(0.558)	(0.533)	(0.994)
$Lvol_{c,t}$		1.536***	1.825***	1.826***	1.338**	3.201***
		(0.569)	(0.575)	(0.575)	(0.546)	(1.019)
$\Delta IR_{c,t}$		0.004	0.001	0.001	−0.001	0.001
		(0.008)	(0.008)	(0.008)	(0.012)	(0.005)
$FXRet_{c,t}$		0.070	0.091	0.090	0.053	0.160***
		(0.070)	(0.072)	(0.072)	(0.090)	(0.055)
$FXvol_{c,t}$		−2.418*	−2.436*	−2.408*	−0.528	−6.367***
		(1.322)	(1.401)	(1.392)	(1.825)	(2.366)
$Logsize_{i,t-1}$			0.015***	0.013***	0.016***	0.009**
			(0.002)	(0.002)	(0.002)	(0.004)
$Vol_{i,t-1}$			−0.029	−0.024	−0.035	0.727***
			(0.036)	(0.036)	(0.037)	(0.179)
$Turnover_{i,t-1}$			−0.001	−0.001	−0.020***	0.028***
			(0.003)	(0.003)	(0.005)	(0.004)
$Leverage_{i,t-1}$				−0.008	−0.002	−0.030***
				(0.005)	(0.006)	(0.009)
$BM_{i,t-1}$				−0.005**	−0.006**	−0.003
				(0.002)	(0.003)	(0.003)
$PRratio_{i,t-1}$				0.036***	0.032***	0.055***
				(0.003)	(0.004)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,258,641	1,258,641	1,258,641	1,258,641	972,611	286,030
R^2	0.030	0.031	0.032	0.033	0.034	0.033

average foreign institutional ownership (5.07%) compared to domestic ownership (2.44%). At the firm-institution level, the average value of the indicator variable FOR is 0.463. Lastly, among approximately 13,145 institutions, investment advisors represent the most dominant institutional type, followed by hedge funds. Banks hold the largest average number of stocks, trailed by endowments and pension funds.

Table 3
Parameter values in the baseline model.

Parameter	Symbol	Value
Risk-free rate	r	2%
Number of assets	n	10
Mean payoff	$\bar{z}$	10 for all i
Vol. of asset payoffs	σ_i	linear from 3 to 2
Mean payoff, supply	$\bar{x}_i$	linear from 1 to 2
Vol. of noise shocks	σ_{xi}	0.2 coefficient of variation for all i
Risk aversion	ρ_R, ρ_I	1.1, 0.9
Information capacities	$\frac{K_R}{K_I}$	0.6 for *Developed*, 0.3 for *Emerging*
Total information capacity		3.4 for *Developed*, 3.9 for *Emerging*
and investor masses	λ	0.182 for *Developed*, 0.0075 for *Emerging*

3. Institutional investor flows: Aggregate and the cross-section

In this section, we present our baseline empirical results on the relationship between institutional flows and global volatility. We first present the effect of global volatility on institutional flows aggregated at the firm level. Then, we zoom in on investor-firm-level effects. We study both effects in the overall sample and also separately for firms in developed and emerging markets. The firm-level analysis allows us to establish benchmark responses for our disaggregated results, and facilitates comparisons between the individual investor-level and aggregated firm-level responses.

In our first test, we estimate the impact of global volatility on firm-level institutional flows using quarterly data:

$$\Delta LogIO_{i,t} = a_0 + a_1 Gvol_t + a_2 \text{Country Controls}_{i,t} + a_3 \text{Firm Controls}_{i,t-1} + \mu_i + \epsilon_{i,t} \quad (1)$$

where $\Delta logIO_{i,t}$ is a quarterly change in natural logarithm of institutional ownership of firm i between quarter $t-1$ and t. $Country\ Controls$ is a vector of economy-level controls affecting international capital flows, including $Lvol$, ΔIR, $FXret$, and $FXvol$. We motivate factors, such as interest rate and exchange rate by the work of Forbes and Warnock (2012) and Fratzscher (2012); local stock market volatility has been previously used by Rey (2013) and Gourio et al. (2015). $Firm\ Controls$ is a vector of firm controls including $Logsize$, $Volatility$, $Turnover$, $Leverage$, $Book\ to\ Market\ ratio$, and $PRratio$, all measured with one quarter lag. Using these controls allows us to rule out explanations based on time-varying firm-specific risk exposures. Many of these controls have been used in prior studies as important determinants of global portfolio flows (e.g., Gompers and Metrick, 2001; Ferreira and Matos, 2008; Kacperczyk et al., 2021). We also account for time-invariant firm-level heterogeneity using firm-fixed effects, which addresses the possibility that fund flows could simply reflect stable preferences for particular assets. Given that individual firms in our sample do not change their primary location, including firm-fixed effects also absorbs economy level time-invariant heterogeneity. We double cluster standard errors at firm and year/quarter level. Our coefficient of interest is a_1. We present the results in Table 2.

In columns 1-4, we consider all firms in our sample. We progressively saturate the model with more controls. In column 1, we only include $Gvol$ and firm fixed-effects; in column 2, we additionally include country-level variables; in column 3, we further include firm-level controls related to trading; in column 4, we include all other controls. Across all the specifications, the results indicate a statistically strong negative relationship between $Gvol$ and institutional flows as the coefficient is significant at the 1% level. Further, the inclusion of the different controls does not affect the coefficient of $Gvol$ markedly, although, as expected, the macro-level variables explain the most variability of the model. For the most comprehensive specification, a one-standard-deviation increase in $Gvol$ is associated with about 1.9 percentage points drop in institutional flows. We further report the results in subsamples of firms in developed (in column 5) and emerging economies (in column 6). We find a statistically significant and negative effect in both markets. In terms of economic magnitudes, the results are significantly stronger in a sample of firms in emerging markets with the respective effects equal to 1.7 and 2.4 percentage-point drops. Overall, the results suggest that institutional investors reduce their equity positions in times of high global volatility even though the economic value of the effect is relatively modest.

Our firm-level results provide a useful benchmark of average responses aggregated across aggregated investors, but are an imperfect measure of individual investor-level responses–our main object of study–in the presence of significant heterogeneity among investors. In particular, some investors may reduce their stock holdings because they are generally more risk averse or they face different regulatory constraints. In turn, other investors may increase their holdings in response to the shocks. In addition, investors may differ in their preferences for holding different stocks. If the composition of investors changes with global stress, our firm-level results would capture the combined investor-specific and composition effects, and not specific investor-level elasticities. The granularity of our data allows us to unpack many of these confounding effects, since we observe changes in firm-level equity positions separately for each institutional investor. More importantly, using investor-level data allows us to isolate the discretionary aspect of flows which is one of the unique features of our study. To this end, we estimate the following regression model using investor-firm-level data:

$$\Delta LogIO_{i,j,t} = a_0 + a_1 Gvol_t + a_2 \text{Country Controls}_{i,t} + a_3 \text{Firm Controls}_{i,t-1} + a_4 \text{Investor Controls}_{i,t-1} + \mu_{i,j} + \epsilon_{i,j,t} \quad (2)$$

The controls of the model mimic those of the firm-level regression, with the exception that the current model also includes institutional investors' assets under management ($log(InsAUM)$) and their portfolio returns ($InsRet$). The measures are motivated by a large literature shows that fund flows are predictable from past fund performance, such as Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998). Further, investor portfolio size is negatively correlated with portfolio performance and has strong effect on stock investing Chen et al. (2004). Also, in some specifications, we include investor and investor×firm-fixed effects ($\mu_{i,j}$). The coefficient of interest is a_1. Table 4 shows the results for the unconditional sample and the samples based on firms from developed and emerging markets.[7]

As in Table 2, we first show the effects in the model with all firm-investors that gets progressively saturated with different controls (columns 1-4). As before, we do not find the different controls to have a material impact on our estimated coefficient of $Gvol$ though we note that country-level variables have the most effect on the estimated coefficient. A comparison of the corresponding columns (1-4) between Tables 2 and 4 gives a sense of the large extent of investor heterogeneity. Comparing columns 4 in each table, the disaggregated results imply a response that is almost three times as large as the aggregated firm-level responses, suggesting that large holdings investors may be characterized by lower elasticities and/or large entry and exit responses among investors. We characterize some aspects of this heterogeneity in the coming sections.

In columns 4, 7, and 10, we report the results for the specification with full set of control variables and firm-fixed effects. We find that

[7] As an alternative, in this and subsequent tests, we also employ the change in ownership, $(IO_t - IO_{t-1})$, as a dependent variable. The results are qualitatively similar, as reported in Appendix C. It is worth noting that in the investor-firm specifications, some observations with new entry share holdings and liquidated share holdings contain holdings that are zero in either the current or previous period. For these observations, the zero values would be omitted when computing the log change or percentage change. To avoid this, we replace these zero values with 1 (i.e., holding one share) to preserve these observations in the data. This enables us to compare the coefficient estimates from firm-level and investor-firm level regressions.

Table 4
Global volatility and capital flows: Investor-firm-level heterogeneity.
This table presents the investor-firm-level regression results for the relation between global volatility and institutional ownership changes based on investor-firm-quarter sample observed between 2000 and 2020. We report the results for the full sample, as well as developed and emerging markets sub-samples. The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variable is global volatility ($Gvol$). Control variables include firm characteristics ($Logsize$, Vol, $Turnover$, $Leverage$, BM, $PRratio$) and macro variables ($Lvol$, ΔIR, $FXRet$, $FXvol$), investor characteristic variables ($Log(InsAUM)$ and $InsRet$) are also included. The data section provides detailed definitions of these variables. Section 2 provides detailed definitions of these variables. Regression models include firm, investor, and firm×investor-fixed effects. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ALL						Developed			Emerging		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\Delta Log(IO)_{i,j,t}$											
$Gvol_t$	−9.876***	−12.209***	−10.867***	−11.226***	−10.143***	−16.268**	−11.422***	−10.270***	−15.996**	−11.878**	−13.223**	−27.025**
	(1.809)	(2.562)	(2.956)	(2.744)	(2.481)	(7.602)	(2.895)	(2.613)	(7.396)	(5.282)	(5.639)	(12.273)
$Lvol_{c,t}$		2.295	2.351	2.376	−0.242	−4.265	1.596	−1.186	−5.678	15.056***	15.351***	19.544***
		(2.150)	(2.250)	(2.174)	(1.920)	(4.627)	(2.283)	(2.023)	(4.874)	(4.932)	(4.659)	(6.933)
$\Delta IR_{c,t}$		−0.030	−0.038	−0.043	−0.030	−0.031	−0.045	−0.034	−0.041	−0.043**	−0.015	0.017
		(0.043)	(0.036)	(0.034)	(0.033)	(0.077)	(0.039)	(0.038)	(0.088)	(0.020)	(0.021)	(0.045)
$FXRet_{c,t}$		0.520**	0.483*	0.434*	0.283	0.260	0.276	0.141	0.117	1.133***	0.978***	0.844
		(0.261)	(0.248)	(0.237)	(0.205)	(0.413)	(0.259)	(0.227)	(0.427)	(0.309)	(0.299)	(0.554)
$FXvol_{c,t}$		−1.742	−2.708	−4.130	−6.093	12.436	3.807	1.318	24.035	−49.625***	−51.874***	−57.457***
		(5.969)	(6.134)	(5.723)	(5.278)	(14.33)	(6.290)	(5.962)	(15.376)	(11.263)	(11.150)	(20.020)
$Logsize_{i,t-1}$			−0.054***	−0.077***	−0.030**	−0.148***	−0.080***	−0.035***	−0.157***	−0.021	0.038	−0.021
			(0.012)	(0.013)	(0.011)	(0.023)	(0.013)	(0.011)	(0.022)	(0.028)	(0.028)	(0.044)
$Vol_{i,t-1}$			0.183	0.290	0.174	0.337	0.261	0.157	0.266	3.223**	2.624**	5.165**
			(0.215)	(0.218)	(0.197)	(0.527)	(0.220)	(0.200)	(0.524)	(1.387)	(1.148)	(2.091)
$Turnover_{i,t-1}$			−0.258***	−0.258***	−0.260***	−0.361***	−0.283***	−0.284***	−0.398***	0.169***	0.162***	0.25***
			(0.021)	(0.021)	(0.020)	(0.038)	(0.023)	(0.021)	(0.040)	(0.046)	(0.043)	(0.078)
$InsRet_{j,t-1}$			0.225*	0.233*	0.249*	0.285	0.203*	0.210	0.246	0.415**	0.515***	0.519
			(0.130)	(0.125)	(0.135)	(0.293)	(0.121)	(0.132)	(0.287)	(0.169)	(0.185)	(0.364)
$Leverage_{i,t-1}$				−0.022	0.014	−0.152**	−0.013	0.022	−0.135**	−0.139*	−0.140*	−0.371***
				(0.033)	(0.031)	(0.063)	(0.034)	(0.033)	(0.064)	(0.081)	(0.080)	(0.123)
$BM_{i,t-1}$				−0.137***	−0.136***	−0.280***	−0.143***	−0.145***	−0.285***	−0.035	−0.028	−0.143**
				(0.028)	(0.026)	(0.049)	(0.029)	(0.026)	(0.051)	(0.038)	(0.036)	(0.056)
$PRratio_{i,t-1}$				0.105***	0.085***	0.119***	0.094***	0.073***	0.097***	0.197***	0.209***	0.34***
				(0.022)	(0.021)	(0.034)	(0.023)	(0.022)	(0.037)	(0.068)	(0.069)	(0.123)
$Log(InsAUM)_{j,t-1}$				−0.019***	−0.275***	−0.466***	−0.021***	−0.275***	−0.459***	0.001	−0.318***	−0.541***
				(0.002)	(0.014)	(0.024)	(0.003)	(0.014)	(0.024)	(0.003)	(0.024)	(0.038)
Firm FE	Yes	Yes	Yes	Yes	Yes		Yes	Yes		Yes	Yes	
Investor FE					Yes			Yes			Yes	
Firm × Investor FE						Yes			Yes			Yes
Observations	116,605,737	116,605,737	116,605,737	116,605,737	116,605,737	116,605,737	106,693,785	106,693,785	106,693,785	9,911,952	9,911,952	9,911,952
R^2	0.002	0.002	0.002	0.003	0.009	0.042	0.003	0.009	0.043	0.003	0.01	0.036

the effect of global volatility increases in magnitude across all sets of firms. For the unconditional sample (column 4), we find a roughly 5.6 percentage point decrease in stock flows as a function of one-standard-deviation increase in global volatility. This result suggests that investors with a smaller sensitivity to global shocks are more likely to participate in the market during periods of high volatility. Relative to the results based on firm-level data, the effect is about three times larger for the sample of firms in both developed and emerging markets.

In columns 5, 8, and 11, we further include investor-fixed effects, which allows us to control for time-invariant investor characteristics. In particular, this specification absorbs variation due to any stable institutional mandates. Across all specifications, we find only a slightly different coefficient relative to the specifications with firm-fixed effects. These results suggest that time-invariant investor characteristics, such as managerial skill or background, or permanent institutional constraints, are not significant predictors of the volatility effect.

Finally, in columns 6, 9, and 12, we report the results for the regressions that additionally include firm×investor-fixed effects. Including these fixed effects accounts for a possible selection of institutions into specific stocks that could vary with the global volatility shocks. As an example, margin constraints faced by individual investors typically differ for various stocks. Similarly, asset managers may exhibit heterogeneous firm-specific preferences towards stocks, due to home bias or informational advantage. When we include the additional fixed effects, we find that the coefficient of $Gvol$ increases by roughly 50% for the sample of all firms and firms in developed markets, and it doubles for the sample of firms in emerging markets. In terms of economic magnitudes, institutional investors tend to reduce their stock flows in both samples by about 8 percentage points per one-standard-deviation increase in global volatility. The effect becomes even stronger for the sample of firms in emerging markets, where the corresponding reduction in ownership equals about 13.5 percentage points. The results emphasize the importance of controlling for firm-investor variation in uncovering the economic mechanism behind investor responses. More broadly, they indicate that any evidence based on aggregate data may mask significant investor heterogeneity, making it difficult to pin down the precise sensitivity of individual investors to global volatility shocks. All in, the effects we estimate at the firm level are significantly muted relative to those at the investor level, which suggests a significant selection of investors into specific stocks.

4. The economic mechanism

Our empirical analyses so far establish a strong empirical association between the measure of global return volatility and institutional investors' holdings. We further show that the strength of this relationship varies between developed and emerging markets and can be primarily attributed to factors that depend on investor individual asset selection choices rather than their responding to non-discretionary factors, such as outside capital flows or differences in organizational mandates. Nonetheless, these findings may be difficult to interpret without a specific economic framework. In this section, we propose and test the mechanism that is consistent with these results. On the theory side, we develop a general equilibrium model of portfolio choice with

Table 5
Institutional ownership and price informativeness.
This table presents the firm-level regression results for the relation between institutional ownership and price informativeness based on the sample of firms observed between 2000 and 2020. We report the results for the full sample, as well as developed and emerging markets sub-samples. The dependent variables are earnings over asset in next quarter ($E_{i,t+1}/A_{i,t}$) and next four quarters ($E_{i,t+1\to4}/A_{i,t}$). The main independent variable is $log(M/A)_{i,t} \times IO_{i,t}$. Control variables include firm characteristics ($Logsize$, Vol, $Turnover$, $Leverage$, BM, and $PRratio$). Section 2 provides detailed definitions of these variables. Regression model includes firm and quarter fixed effects. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ALL		Developed		Emerging	
	(1)	(2)	(3)	(4)	(5)	(6)
	$E_{i,t+1}/A_{i,t}$	$E_{i,t+1\to4}/A_{i,t}$	$E_{i,t+1}/A_{i,t}$	$E_{i,t+1\to4}/A_{i,t}$	$E_{i,t+1}/A_{i,t}$	$E_{i,t+1\to4}/A_{i,t}$
$log(M/A)_{i,t} \times IO_{i,t}$	0.947***	3.681***	1.054***	4.112***	1.064***	5.278***
	(0.052)	(0.221)	(0.058)	(0.241)	(0.171)	(0.816)
$IO_{i,t}$	0.577***	1.800***	0.436***	1.216**	0.712***	2.057**
	(0.094)	(0.453)	(0.107)	(0.516)	(0.203)	(0.932)
$log(M/A)_{i,t}$	0.244***	1.405***	0.053	0.601***	0.917***	4.143***
	(0.050)	(0.163)	(0.056)	(0.190)	(0.056)	(0.187)
$E_{i,t}/A_{i,t}$	0.279***	0.871***	0.287***	0.890***	0.204***	0.652***
	(0.014)	(0.042)	(0.014)	(0.042)	(0.019)	(0.051)
$Logsize_{i,t}$	0.195***	−0.135	0.282***	0.267*	−0.160***	−1.795***
	(0.030)	(0.115)	(0.034)	(0.141)	(0.046)	(0.151)
$Vol_{i,t}$	−0.847***	−2.227*	−1.050***	−3.472**	−2.054	−1.270
	(0.312)	(1.283)	(0.324)	(1.316)	(1.275)	(5.464)
$Turnover_{i,t}$	−0.032	−0.245*	−0.053	−0.308	−0.059*	−0.427***
	(0.032)	(0.139)	(0.043)	(0.192)	(0.033)	(0.140)
$Leverage_{i,t}$	0.531***	2.981***	0.614***	3.459***	0.326**	1.630***
	(0.110)	(0.405)	(0.120)	(0.461)	(0.148)	(0.546)
$BM_{i,t}$	−0.053**	−0.533***	−0.082***	−0.636***	−0.011	−0.422***
	(0.023)	(0.104)	(0.030)	(0.130)	(0.025)	(0.102)
$PRratio_{i,t}$	2.547***	9.217***	2.619***	9.538***	1.978***	6.783***
	(0.105)	(0.463)	(0.116)	(0.497)	(0.183)	(0.753)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	701,773	701,773	526,657	526,657	175,116	175,116
R^2	0.617	0.719	0.629	0.725	0.452	0.614

endogenous information acquisition. The model exploits the following typically observed heterogeneities in the data: institutional investors are more informed about asset-specific fundamental and are less risk averse than retail investors. In addition, investable assets are heterogeneous in terms of their size and volatility. We further assume that the informational gap is bigger in emerging markets. On the empirical side, we use specific predictions of the model to explain potential differences in the responsiveness of portfolio holdings to aggregate volatility shocks both along the asset and investor dimensions. We show that the predictions of the model are consistent with the patterns we observe in the data.

4.1. Model setup

We set up a portfolio choice model in which investors are limited in their ability to process information about asset payoffs. Our framework builds upon the model of Kacperczyk et al. (2019). A continuum of investors of mass one, indexed by j, with investor-specific risk aversion, $\rho_j > 0$, solve a sequence of portfolio choice problems, to maximize mean–variance utility over wealth W_j in each period. The financial market consists of one risk-free asset, with price normalized to 1 and payoff r, and $n > 1$ risky assets, indexed by i, with prices p_i, and independent payoffs $z_i = \bar{z} + \varepsilon_i$, with $\varepsilon_i \sim \mathcal{N}\left(0, \sigma_i^2\right)$.[8] The risk-free asset has unlimited supply, and each risky asset has fixed supply, $\bar{x}_i$. For each risky asset, non-optimizing "noise traders" trade for reasons orthogonal to prices and payoffs (e.g., liquidity, hedging, or life cycle), such that the net supply available to the (optimizing) investors is $x_i = \bar{x}_i + \nu_i$, with $\nu_i \sim \mathcal{N}\left(0, \sigma_{xi}^2\right)$, independent of payoffs and across assets.

Following Admati (1985), we conjecture and later verify in equilibrium that the price of an asset i is of a form $p_i = a_i + b_i\varepsilon_i - c_i\nu_i$, with coefficients $a_i, b_i, c_i \geq 0$.

Investors know the distributions of the shocks, but not their realizations (ε_i, ν_i). Prior to making their portfolio decisions, investors can obtain information about some, or all of the risky asset payoffs, in the form of signals. The informativeness of these signals is constrained by each investor's capacity to process information. We consider two investor types: mass λ of investors are institutional investors, with information capacity K_I, and mass $1-\lambda$ of investors are retail investors, with information capacity $K_R < K_I$. Our assumption about the relative differences in information capacity across investors is consistent with the ample empirical evidence in the literature, which shows that institutional investors, on average, are more informed than retail investors.

Evidence on information asymmetry. To validate this assumption, we use empirical methodology from the literature (Kacperczyk et al., 2021) and study the link between institutional ownership (IO) and price informativeness (PI) at the stock level. In this model, PI is defined as the sensitivity of future earnings to current stock prices. We estimate the following pooled regression model using firm-level quarterly frequency data:

$$E_{i,t+h}/A_{i,t} = a_0 + a_1 log(M/A)_{i,t} \times IO_{i,t} + a_2 log(M/A)_{i,t} + \\ + a_3 IO_{i,t} + a_4 E_{i,t}/A_{i,t} + a_5 \text{Firm Controls}_{i,t} + \mu_i + \mu_t + \epsilon_{i,t+h} \quad (3)$$

In the above model, we measure earnings over next quarter and over next four quarters. $log(M/A)_{i,t}$ is the natural logarithm of market capitalization ($M_{i,t}$) to total assets ($A_{i,t}$). $(E/A)_{i,t}$ is earnings before interest and taxes ($EBIT$), divided by total assets. Our coefficients of interest are a_1 and a_2, with a_2 showing the value of PI for companies whose IO is equal to zero. We present the results in Table 5, both for the aggregate sample of stocks, as well as separately for stocks in developed and emerging markets.

[8] Under simplifying assumptions of independence of signals across assets, assuming independent payoffs is without loss of generality. See Van Nieuwerburgh and Veldkamp (2010) for a discussion of how to orthogonalize correlated assets under such assumptions.

The results indicate a strong positive association between the level of institutional ownership and price informativeness, both in the short and the long run. The results are particularly strong for the subsample of stocks in emerging markets, consistent with our assumption that institutional ownership has a bigger informational content in emerging markets. Overall, the empirical results provide strong support for our modeling assumptions.

Our notion of greater information capacity maps to a setting in which investors have more resources to gather and process news about different assets. In our model, this translates into signals that track the realized payoffs with higher precision. Differently, bounded capacity limits investors' ability to reduce uncertainty about payoffs. Investors choose how to allocate learning capacity across different assets. We use the reduction in the entropy (Shannon, 1948) of the payoffs conditional on the signals as a measure of how much capacity the chosen signals consume.[9]

Individual optimization. Optimization occurs in two stages. In the first stage, investors solve their information acquisition problem, and in the second stage, they choose portfolio holdings. We first solve the optimal portfolio choice in the second stage, for a given signal choice. We then solve for the ex-ante optimal signal choice.

Given prices and posterior beliefs, the investor chooses portfolio holdings to solve

$$U_j = \max_{\{q_{ji}\}_{i=1}^n} E_j\left(W_j\right) - \frac{\rho_j}{2} V_j\left(W_j\right) \tag{4}$$

$$s.t.\ \ W_j = r\left(W_{0j} - \sum_{i=1}^n q_{ji} p_i\right) + \sum_{i=1}^n q_{ji} z_i, \tag{5}$$

where E_j and V_j denote the mean and variance conditional on investor j's information set, and W_{0j} is initial wealth. Optimal portfolio holdings depend on the mean $\widehat{\mu}_{ji}$ and variance $\widehat{\sigma}^2_{ji}$ of investor j's posterior beliefs about the payoff z_i, and is given by $q_{ji} = \frac{\widehat{\mu}_{ji} - rp_i}{\rho_j \widehat{\sigma}^2_{ji}}$.

Given the optimal portfolio holdings as a function of beliefs, the ex-ante optimal distribution of signals maximizes ex-ante expected utility, $E_{0j}\left[U_j\right] = \frac{1}{2\rho_j} E_{0j}\left[\sum_{i=1}^n \frac{\left(\widehat{\mu}_{ji} - rp_i\right)^2}{\widehat{\sigma}^2_{ji}}\right]$. The choice of the vector of signals $s_j = (s_{j1}, \ldots, s_{jn})$ about the vector of payoffs $z = (z_1, \ldots, z_n)$ is subject to the constraint $I\left(z; s_j\right) \le K_j$, where K_j is the investor's capacity for processing information about the assets and $I\left(z; s_j\right)$ quantifies the reduction in the entropy of the payoffs, conditional on the vector of signals (defined below).

Following Kacperczyk et al. (2019), we assume that the signals s_{ji} are independent across assets and investors. Then, the total quantity of information obtained by an investor is the sum of the quantities of information obtained for each asset, $I\left(z_i; s_{ji}\right)$. In this case, the investor's problem boils down to choosing the precision of posterior beliefs for each asset to solve[10]

$$\max_{\left\{\widehat{\sigma}^2_{ji}\right\}_{i=1}^n} \sum_{i=1}^n G_i \frac{\sigma_i^2}{\widehat{\sigma}^2_{ji}} \quad s.t.\ \ \frac{1}{2}\sum_{i=1}^n \log\left(\frac{\sigma_i^2}{\widehat{\sigma}^2_{ji}}\right) \le K_j, \tag{6}$$

$$G_i \equiv (1 - rb_i)^2 + \frac{r^2 c_i^2 \sigma_{xi}^2}{\sigma_i^2} + \frac{(\bar{z} - ra_i)^2}{\sigma_i^2}, \tag{7}$$

where G_i are the utility gains from learning about asset i. These gains are a function of equilibrium prices and asset characteristics only; they are common across investor types, and taken as given by each investor.

The linear objective and convex constraint imply that each investor specializes, monitoring only one asset, regardless of her level of sophistication. For all other assets, portfolio holdings are determined by prior beliefs. If there are multiple assets that are tied for the highest gain, the investor randomizes among them, with probabilities that are determined in equilibrium, but they continue to allocate all capacity to a single asset (see Lemma 1 in Appendix D.1).

Given the solution to the individual optimization problem, equilibrium prices are linear combinations of the shocks. The price of asset i is given by $p_i = a_i + b_i \varepsilon_i - c_i \nu_i$, with (for derivation, see Appendix D.2)

$$a_i = \frac{1}{r}\left[\bar{z} - \frac{\sigma_i^2 \bar{x}_i}{(\bar{\lambda} + \Phi_i)}\right],\ \ b_i = \frac{\Phi_i}{r(\bar{\lambda} + \Phi_i)},\ \ c_i = \frac{\sigma_i^2}{r(\bar{\lambda} + \Phi_i)}, \tag{8}$$

$$\Phi_i \equiv \frac{m_{Ii}}{\rho_I}(e^{2K_I} - 1) + \frac{m_{Ri}}{\rho_R}(e^{2K_R} - 1),$$

$$\bar{\lambda} \equiv \frac{\lambda}{\rho_I} + \frac{1-\lambda}{\rho_R},$$

where Φ_i measures the information capacity allocated to learning about asset i in equilibrium, and $m_{Ii} \le \lambda, m_{Ri} \le 1 - \lambda$ are the masses of institutional and retail investors who choose to learn about asset i.

Prices reflect payoff and supply shocks, with relative importance determined by the amount of attention allocated to each asset, Φ_i. If there is no learning, the price only reflects the supply shock ν_i and $b_i = 0$. As the attention allocated to an asset increases, the price co-moves more with the payoff.

Main drivers of trades and learning. Given the price coefficients, the gain from learning about asset i is given by

$$G_i = \frac{\bar{\lambda} + \xi_i}{(\bar{\lambda} + \Phi_i)^2}, \tag{9}$$

where $\xi_i \equiv \sigma_i^2(\sigma_{xi}^2 + \bar{x}_i^2)$ summarizes asset-specific exogenous part of the gain.

This gain is increasing in the fundamental volatility of the asset σ_i^2 and supply $\bar{x}_i$, which gives clear preference of investors to learn about assets with (i) large supply or (ii) high volatility.

Intuitively, the average excess return on highly volatile or large-supply assets is higher, due to their lower average price. This can be seen through a_i in Eq. (8): for the same amount of learning Φ_i, an asset with a higher supply $\bar{x}_i$ or higher volatility σ_i will have a lower average price, which depends only on a_i. However, capturing that higher return requires lowering the possibility of mistakes by investing information capacity into that asset. Hence, the returns from investing capacity in high volatility or size assets is higher for the same Φ_i. We can also see from the price coefficients why the pure size effect can be potentially quantitatively dominant: compared with large-size assets, high-volatility assets have an additional disadvantage that their loading on the noise term, c_i, is also higher, and so they are characterized by more noisy excess returns.

Equilibrium. Without loss of generality, let assets be indexed so that $\xi_i > \xi_{i+1}$. Then, in equilibrium, an endogenously determined number $k \le n$ of the first k assets is learned about, with masses m_{Ii}, m_{Ri} of investors pinned down by the condition that the gain is equalized among assets that are learned about, i.e. $G_i = G_l$ for $i, l \le k$ and $G_k > G_i$ for $i > k$. These results are derived in Appendix D.3.

The equilibrium gains from learning are asset-specific and depend only on the properties of the asset, ξ_i, and on the amount of attention devoted to that asset, across all investors, Φ_i. The model uniquely pins down the number of assets that are learned about and the amount of attention allocated to each asset. Aggregate capacity in the economy may be high enough that in equilibrium it is spread across multiple assets. In this case, each investor continues to allocate her entire capacity to a single asset, but the investor randomizes, with the probability of learning about each asset being determined by the equilibrium conditions in Lemma 2 in Appendix D.3.

[9] Starting with Sims (2003), entropy reduction has become a frequently used measure of information in a variety of contexts in economics. This learning process captures the key trade-offs investors face when deciding how to allocate their limited capacity across multiple investment decisions, as a function of their objective and of the risks they face.

[10] The investor's objective omits terms from the expected utility function that do not affect the optimization.

With heterogeneous investor capacity, the model does not pin down how much attention each investor class contributes: All that matters is the total capacity Φ_i allocated to each asset. In our analysis, we follow Kacperczyk et al. (2019), and focus on a symmetric equilibrium allocation, in which institutional investors contribute capacity in proportion to their size in the population, so that $\frac{m_{Ii}}{\lambda} = \frac{m_{Ri}}{1-\lambda}$. This assumption is motivated by our result that the gains from learning are the same for the two investor types, as it is not obvious ex ante why they would choose different strategies.

4.2. Numerical results

In this section, we present the numerical results from the model. The simplicity of the model prevents a full calibration exercise, however, below, we provide numerical examples that can be related qualitatively to the patterns we look for in the data.

Parameter choices. In the calibration of the model, we set the risk-free rate to 2%, normalize $\bar{z} = 10$ and $n = 10$. We set $\bar{x}_i$ to be uniformly distributed along the $[1, 2]$ interval, set the coefficient of variation of the noise shock to be 0.2, and set the volatility of the payoff shock to be negatively related with the size and vary between 3 for the smallest stock to 2 for the largest stock. As for the coefficient of risk aversion, we set the retail risk aversion coefficient to 1.1, and the institutional risk aversion coefficient to 0.9, reflecting the observation that retail portfolios are typically less diversified and retail investors can be subject to additional uninsurable shocks relative to institutional investors. Finally, we choose the total information capacity in the model[11] to have equilibrium learning about all assets, and match the average market excess return of 4.3%.[12] On top of these parameters, we choose the ratio of retail to institutional information capacity to approximate two scenarios, *Developed Markets* and *Emerging Markets*. For the *Developed Markets* parameterization, we pick the information capacity of retail and institutional investors to be relatively close, with K_R/K_I equal to 60%, while in the *Emerging Markets* parameterization we set that ratio at 30%. This choice reflects the idea that institutional investors are more sophisticated relative to retail investors in emerging economies compared to developed economies. These two targets are paired with targets for institutional ownership share in developed markets of 27% and emerging markets of 7.5%. This strategy pins down the capacities K_I, K_R, and institutional size λ. Summary of the parameters is reported in Table 3.

To analyze the model's response of investors' portfolios to an aggregate increase in the volatility of all assets' payoffs, we introduce a shock to the volatility of all assets, which we assume changes from σ_i to $\tilde{\sigma}_i = 1.2\sigma_i$, and at the same time a shock to the institutional risk aversion so that it goes up from 0.9 to 1. What that change in risk aversion reflects is that institutional investors are more exposed to asset market volatility than retail investors.[13] We subsequently compute the change in investors' asset ownership in response to the shock. Fig. 1 presents the results. Institutional investors increase their holdings of the large-supply assets and reduce holdings of the small-supply assets relative to retail investors. This relocation is dictated by the fact that large assets provide more information rents, as implied by Eq. (9). In response to the shock, *ceteris paribus*, the gain G_i increases more for large assets than small assets, and investors reoptimize their learning towards them.[14] Since institutional investors have larger capacity, in equilibrium, their relocation of learning implies the largest change in ownership. The magnitude of these effects crucially depends on the heterogeneity in information capacity across investors. In the *Developed Markets* parameterization, investors are closer to each other in terms of capacity, and the results are quantitatively smaller. On the other hand, in the *Emerging Markets* parameterization, where differences between institutional and retail investors are larger, the response is much more pronounced. This result points to a potential mechanism behind the heterogeneous responses between emerging and developed markets in the data.

The crucial role of endogenous learning choice and hence discretionary portfolio reallocation can be demonstrated by studying the model's response to the volatility shock under the counterfactual assumption that learning is not permitted to be reoptimized, as presented in Fig. 2. In that case, we observe the average relative drop in institutional ownership relative to retail (Panels A and B), and almost no reallocation across assets (Panels C and D). In fact, in this case, if anything, institutional ownership shifts relatively more towards small assets. Empirically, such behavior would be mostly absorbed by the fund×time fixed effects and would not show up in our cross-sectional estimates.

Our final prediction pertains to the cross-sectional stock turnover. In Fig. 3, we demonstrate the relationship between stock turnover and institutional ownership in the cross-section, comparing the low- and high-volatility equilibria. Turnover displays a pronounced positive correlation with institutional ownership and uniformly decreases in the high-volatility equilibrium. The cross-sectional positive association between ownership and turnover is intuitive, as when a larger fraction of highly sophisticated investors trade a given asset, they react more strongly to their better quality signals, implying larger reallocations of ownership. On the other hand, higher aggregate volatility makes posterior beliefs more noisy, as the informational environment becomes more uncertain. As a result, informed traders react to their private signals less intensively.

4.3. Additional evidence on information-based channel

Our theoretical framework in the previous section offers direct testable predictions that we can evaluate in the data. In particular, our model predicts that, in times of heightened aggregate uncertainty, investors who are more informed, such as institutional investors, reduce their exposure to equity markets, more so for small-size assets. In turn, investors who are less informed, such as retail investors, take the reverse positions. The model further predicts that the difference between the two responses should increase with the informational gap between the two investor groups. Our analysis in Section 3 proxies for this gap by comparing developed and emerging markets, and corroborates the validity of theoretical predictions in the data. In this section, we discuss additional tests in support of the postulated economic mechanism. First, we exploit asset heterogeneity in terms of size and volatility, which offers a more granular and direct way of testing our economic mechanism. Second, using this heterogeneity, we provide additional cross-sectional evidence with respect to economic development or location of the firm. Finally, we present results in which asset heterogeneity intersects with heterogeneity among investors in terms of their informational sophistication.

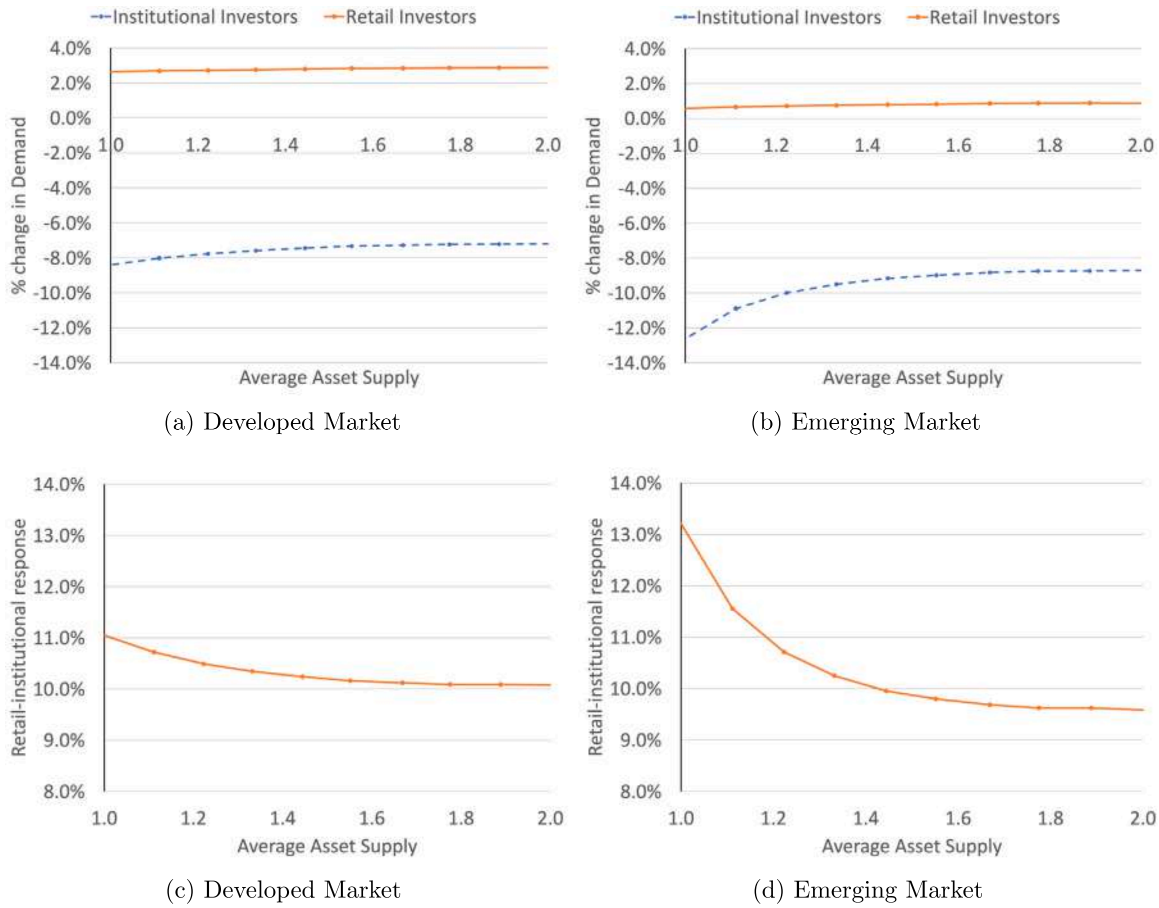
The role of asset heterogeneity. In the model with endogenous information choices, investors who are endowed with information capacity respond to an increased aggregate volatility shock by reducing their position in assets that are small or less volatile and increasing their positions in assets that are large and more volatile. This reallocation process is a different form of a classical flight-to-safety mechanism. In our paper, we measure asset size using stock market capitalization, and asset volatility using stock return volatility. An important element of

[11] Proxied by ϕ above.

[12] This is the market real excess return in the U.S. net of the 3-month T-bill rate over the period 2000–2020.

[13] Ample literature analyzes models with time-varying risk aversion and related evidence based on options-implied volatility, e.g. Campbell and Cochrane (1999), Bollerslev et al. (2011).

[14] Fig. 1 indicates that the preference for size pointed out in Section 4.1 dominates the response to the aggregate volatility shock.



(a) Developed Market
(b) Emerging Market
(c) Developed Market
(d) Emerging Market

Fig. 1. Model Response.

the empirical test of the above mechanism is its reliance on a three-dimensional variation at the firm, investor, and time levels. Observing data at such granularity provides a unique opportunity to identify and control for the discretionary component of investor flows–one that is not driven by time-varying investor-level effects or stable firm-investor effects. In our analysis, we separately consider investment decisions of domestic and foreign institutional investors. Notably, both types of investors are generally more informed than retail ones, so the economic spirit of our tests should remain unchanged.

Formally, we estimate the following regression model that predicts investor flows across stocks:

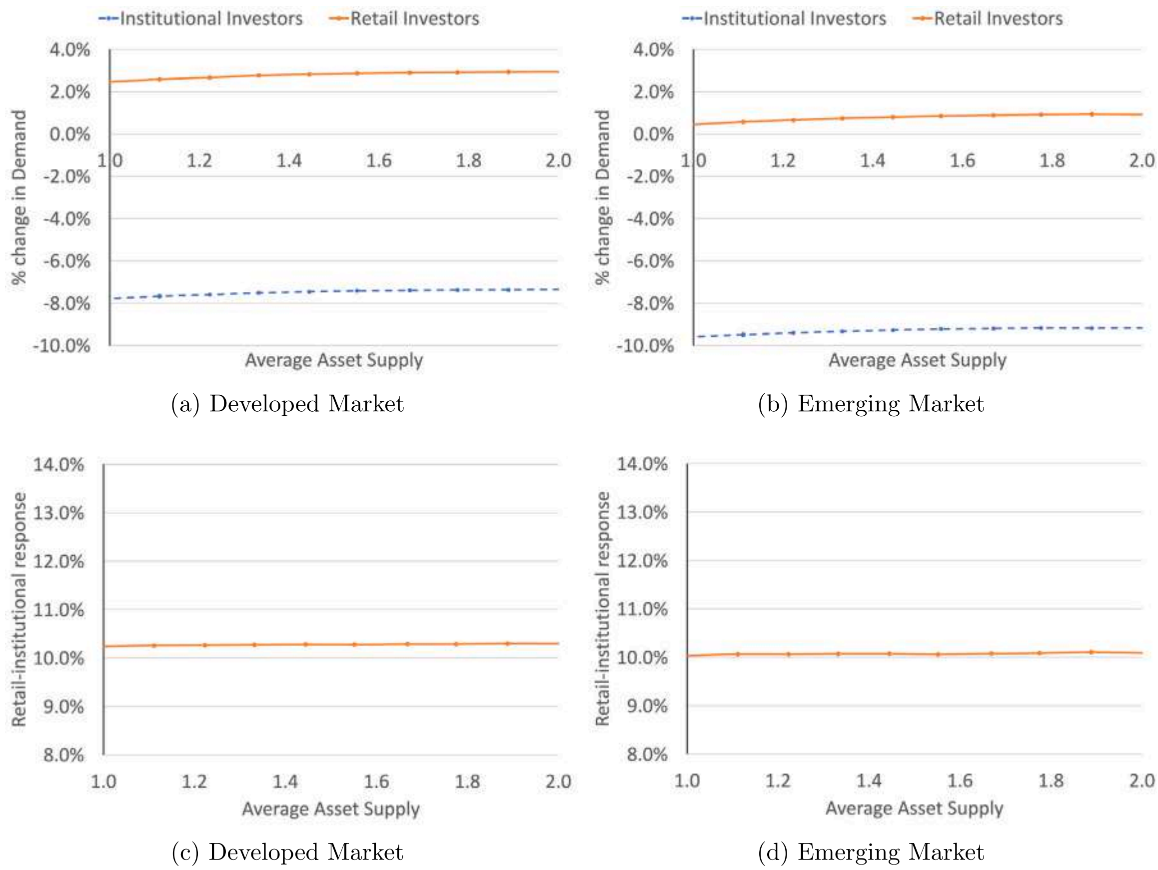
$$\begin{aligned}\Delta LogIO_{i,j,t} = {} & g_0 + g_1\{Gvol_t,\ FOR_{i,j},\ Logsize_{i,t-1}\} \\ & + g_2\{Gvol_t,\ FOR_{i,j},\ Vol_{i,t-1}\} + \\ & + g_3\text{Controls}_{i,t-1} + \mu_{i,j} + \delta_{i,t} + \psi_{j,t} + \epsilon_{i,j,t} \end{aligned} \tag{10}$$

where $\{Gvol_t,\ FOR_{i,j},\ Logsize_{i,t-1}\}$ and $\{Gvol_t,\ FOR_{i,j},\ Vol_{i,t-1}\}$ denote a full set of interaction terms between the three variables in curly brackets. $FOR_{i,j}$ is an indicator variable that is equal to 1 if firm i and investor j are located in different countries. All other controls are defined as before.

The key element of our analysis are different forms of fixed effects along the dimensions of firm×investor ($\mu_{i,j}$), investor×quarter ($\psi_{j,t}$), and firm×quarter ($\delta_{i,t}$). In particular, we consider four different specifications progressively reported in our results: (1) time-varying controls and firm-fixed effects; (2) time-varying controls and firm-investor fixed effects; (3) time-varying controls, firm-investor fixed effects, and investor-quarter fixed effects; (4) firm-investor fixed effects, investor-quarter fixed effects, and firm-quarter fixed effects. Specification (1) aims to capture investor flows that are driven by discretionary and non-discretionary forces of flows; (2) partly absorbs non-discretionary flows driven by stable investor-firm investment policies; (3) additionally absorbs non-discretionary flows due to outside capital inflows/redemptions; (4) uses discretionary flow components and additionally controls for any time-varying firm characteristics. Notably, even though the last specification is the most comprehensive one, it only allows us to identify the flow effects for the group of foreign investors.

We present the findings in Table 6. In columns 1-4, we consider the full sample of firms. For our baseline specification (1), we find a negative and statistically significant effect of global volatility on total flows to small-cap stocks for both domestic (captured by the coefficient of $Gvol$) and foreign investors. The two effects are very similar, as is indicated by the insignificant effect of $Gvol \times FOR$.[15] The effect gets stronger for both groups when using specification (2), but foreign small-cap stocks observe larger withdrawals than do equivalent domestic stocks. Further, the negative effect on foreign small stocks doubles when we consider fully discretionary specifications (3) and (4). The flow effects tend to get reversed as we consider stocks with larger market cap. To understand the economic significance of the effects, note that the standard deviation of $Logsize$ in our sample equals 1.83. Using this number, for specification (1), we observe a reversal of about 30% of the original outflow for domestic stocks (captured by

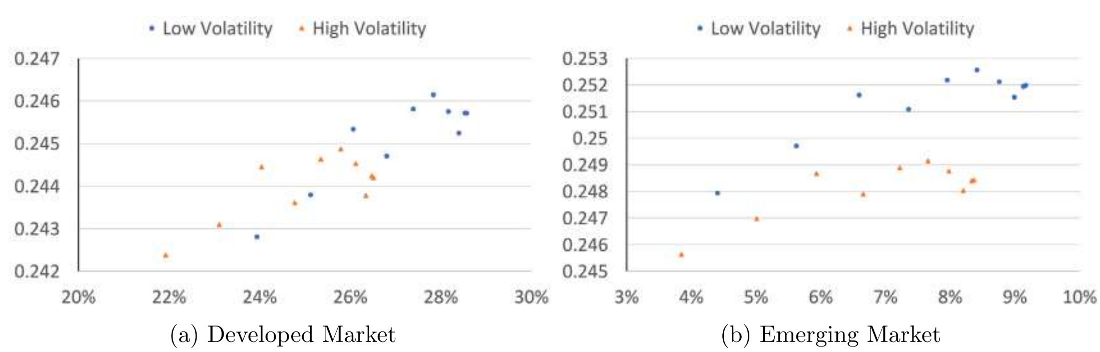
[15] In the Appendix Table C.3, we further show the role of controls in our empirical model. To this end, we successively enter different controls into our model. In addition, in the Appendix Table C.4, we add triple interaction terms with other macro variables. The results indicate a strong robustness of our results to the different sets of controls.



(a) Developed Market (b) Emerging Market

(c) Developed Market (d) Emerging Market

Fig. 2. Model Response: No Discretionary Adjustment.



(a) Developed Market (b) Emerging Market

Fig. 3. Model: Turnover as a Function of Institutional Ownership, Low and High-Volatility Equilibrium.

the coefficient of $Gvol \times Logsize$) and the double of that effect for foreign stocks (coefficient of $Gvol \times FOR \times Logsize$). The effect for domestic stocks remains similar and is slightly larger than the previous one for foreign stocks when we consider specification (2). Notably, when we switch to specification (3), the reversal effect for the sample of domestic stocks is three times larger than that in specification (1). Moreover, for foreign investors, the reversal is quantitatively similar to that in specifications (1) and (2). Finally, the recovery in flows is almost the same for foreign investors when we consider specification (4). Turning to interactions with volatility, the results are less consistent, especially for domestic investors. Still, in the specifications (3) we find a large positive coefficient of the triple interaction term between $Gvol$, FOR, and Vol, indicating a shift of foreign institutions towards more volatile stocks. In sum, taking the specifications that focus on discretionary component of flows, we find results that are consistent with the prediction of our model implying that size and volatility are two asset characteristics which moderate investors' preferences towards global shocks.

To sharpen the economic validity of our postulated mechanism, we further examine the global volatility effects separately for firms in developed and emerging economies. As with the full sample, our results for firms in developed economies, in columns 5 to 8, closely mimic, in terms of economic magnitudes, those for the unconditional sample. However, when focusing on firms in emerging economies, in columns 9 to 12, we observe that the importance of heterogeneity in asset characteristics, both size and volatility, is much more pronounced. Most importantly, for the specification with total flows, in column 9, we find that both domestic and foreign investors retrench somewhat from small-cap companies, but the effects are measured with noise. When we start zooming in on discretionary components, especially column 11, we find that foreign investors' discretionary flows are responding negatively to volatility shocks, especially for small companies. The

Table 6
Global volatility and capital flows: Stock characteristics.
This table presents the investor-firm-level regression results for the relation between global volatility and institutional ownership changes based on the sample of firms between 2000 and 2020. We report the results for the full sample, as well as developed and emerging markets sub-samples. The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variables are global equity return volatility ($Gvol$) and foreign institution indicator FOR, and their interaction terms with firm size ($Logsize$) and stock return volatility (Vol). Control variables are the same as those in Table 4. Regression models include firm, firm×investor, firm × quarter, and investor × quarter fixed effects. Robust standard errors double clustered at the firm and quarter levels are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ALL				Developed				Emerging			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\Delta Log(IO)_{i,j,t}$											
$Gvol_t$	−11.108***	−14.995**			−11.014***	−14.769**			0.275	−5.155		
	(3.078)	(6.515)			(3.099)	(6.518)			(4.995)	(6.975)		
$FOR_{i,j}$	0.120***				0.126***				0.380***			
	(0.019)				(0.019)				(0.052)			
$Gvol_t \times FOR_{i,j}$	−0.847	−4.295	−15.749*	−18.989*	−2.233	−5.099	−16.142**	−18.153*	−13.315***	−23.031**	−15.660	−19.945
	(1.414)	(4.652)	(8.071)	(9.807)	(1.495)	(4.303)	(7.241)	(9.200)	(4.465)	(10.032)	(31.663)	(33.198)
$Gvol_t \times Logsize_{i,t-1}$	2.083***	2.623**	6.941***		2.301***	2.943***	7.030***		1.390	0.617	0.917	
	(0.505)	(1.004)	(2.459)		(0.508)	(1.035)	(2.470)		(0.941)	(1.597)	(1.813)	
$Gvol_t \times Vol_{i,t-1}$	−12.848	−27.563	−118.148***		−8.344	−21.661	−119.736***		−138.103	−246.877	−499.058**	
	(32.414)	(52.733)	(39.856)		(32.183)	(52.890)	(39.915)		(182.721)	(230.787)	(202.257)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	3.379***	4.477***	3.287***	4.224***	3.649***	4.368***	3.313***	4.116***	1.849	5.644***	9.481***	10.515**
	(0.677)	(0.968)	(1.121)	(1.223)	(0.498)	(0.898)	(0.997)	(1.160)	(2.061)	(1.517)	(2.610)	(4.220)
$Gvol_t \times FOR_{i,j} \times Vol_{i,t-1}$	−10.886	−8.215	86.325***	12.472	−12.702	−16.757	84.571***	10.960	−33.069	255.582	232.730	147.238
	(20.418)	(34.099)	(30.851)	(25.085)	(19.766)	(36.058)	(31.814)	(25.514)	(270.710)	(308.635)	(352.806)	(427.359)
$FOR_{i,j} \times Logsize_{i,t-1}$	−0.028***	0.001	0.014	−0.089***	−0.029***	0.009	0.009	−0.087***	0.003	−0.267***	0.065*	0.080
	(0.009)	(0.026)	(0.018)	(0.023)	(0.008)	(0.024)	(0.017)	(0.023)	(0.017)	(0.056)	(0.038)	(0.054)
$FOR_{i,j} \times Vol_{i,t-1}$	0.073	−0.767	−0.858**	−1.103***	0.027	−1.194**	−1.304***	−1.145***	6.105*	8.251	7.740*	6.020
	(0.183)	(0.478)	(0.354)	(0.379)	(0.184)	(0.481)	(0.359)	(0.373)	(3.375)	(5.004)	(4.233)	(4.908)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes				Yes				Yes			
Firm × Investor FE		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Investor × Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Firm × Quarter FE				Yes				Yes				Yes
Observations	116,605,737	116,605,737	116,605,737	116,605,737	106,693,785	106,693,785	106,693,785	106,693,785	9,911,952	9,911,952	9,911,952	9,911,952
R^2	0.003	0.043	0.139	0.191	0.003	0.044	0.145	0.192	0.003	0.036	0.198	0.276

negative effect gets significantly reversed particularly for a sample of large companies and for foreign investors, but less so for domestic investors. Overall, we conclude that institutional investors facing global shocks behave in a way that is consistent with the model of endogenous learning, largely because we observe stronger effects for the discretionary component of flows. The process is quite evenly distributed between domestic and foreign institutions in developed markets. However, foreign institutional investors seem more relevant for equity flows in the context of emerging markets, possibly because such investors are more likely to enjoy stronger informational advantage in such markets.

Evidence from regional markets. Next, we explore the heterogeneity in the data by focusing on different firm locations, divided by region (Americas, Europe, and Asia-Pacific) and degree of economic development. Table 7 presents the results. In Panel A, we consider firms in developed markets and in Panel B in emerging markets. In columns 1, 3, and 5 of each panel we report estimates of regression models based on specification (3), while our models in columns 2, 4, and 6 correspond to specification (4) discussed above. When it comes to developed markets, we find that both types of institutional investors generally increase their holdings in large-cap stocks in periods of high global volatility, but the effect is stronger for foreign investors especially in Europe and Asia Pacific. In turn, foreign investors seem to have a smaller effect in the Americas. When we further consider specification (4), we find that the marginal effect of foreign flows remains very similar for the Americas, while the same effect increases significantly for stocks in Europe and Asia. When we turn to emerging markets, two interesting results emerge. First, the role of domestic investors varies across locations, and it is strongest for stocks in Europe and weakest for stocks in the Americas. In turn, foreign investors matter most in the Americas and their role is similar for stocks in Europe and Asia. Second, the results using specification (4) preserve the consistency of findings in specification (3), with the exception of stocks in Asia for which the effect increases.

We further examine the effects of global shocks on the flow behavior at the country level. Specifically, we relate the average estimate g_1 of the triple-interaction effect in our regression in Table 6, to the level of IMF's Financial Development Index (FDI) and the Financial Institutions Index (FII) of the country in which the firm is located.[16] Because the information across countries has different sparsity, we estimate the regressions for each individual country among developed markets, and for emerging market groups (Americas, Europe, and Asia). We present the relationship graphically in Fig. 4. In the top panel, we report the results for the FDI while the bottom panel is for FII. We observe a strong negative relationship between both indexes and the strength of the elasticity, suggesting that the effect is stronger in countries that are less developed. This result is consistent with our modeling framework and also our findings that companies in emerging markets are more sensitive to aggregate shocks than are companies in developed markets.

The role of investor sophistication. Another dimension along which we can assess the plausibility of our economic mechanism is investor sophistication. In our analysis so far, we have largely explored this dimension using the distinction between institutional and retail investors. However, not all institutions are the same given their different mandates, managerial skills, or size. Specifically, we consider three measures of institutional investors' sophistication: (1) degree of portfolio activeness; (2) managerial skill based on past portfolio returns; and (3) size of assets under management (AUM). *Active Investors* is a group of investors that includes active investment advisors and hedge funds, and *Passive Investors* are passive investment advisors, pension

[16] The FDI index summarizes how developed financial institutions and financial markets are in terms of their depth (size and liquidity), access (ability of individuals and companies to access financial services), and efficiency (ability of institutions to provide financial services at low cost and with sustainable revenues and the level of activity of capital markets). The financial institutions Index (FII) is a component of FDI that measures domestic institutions depth (including banks, pension funds, mutual funds, and insurance sector), access and efficiency. See summary information at https://prosperitydata360.worldbank.org/en/dataset/IMF+FDI.

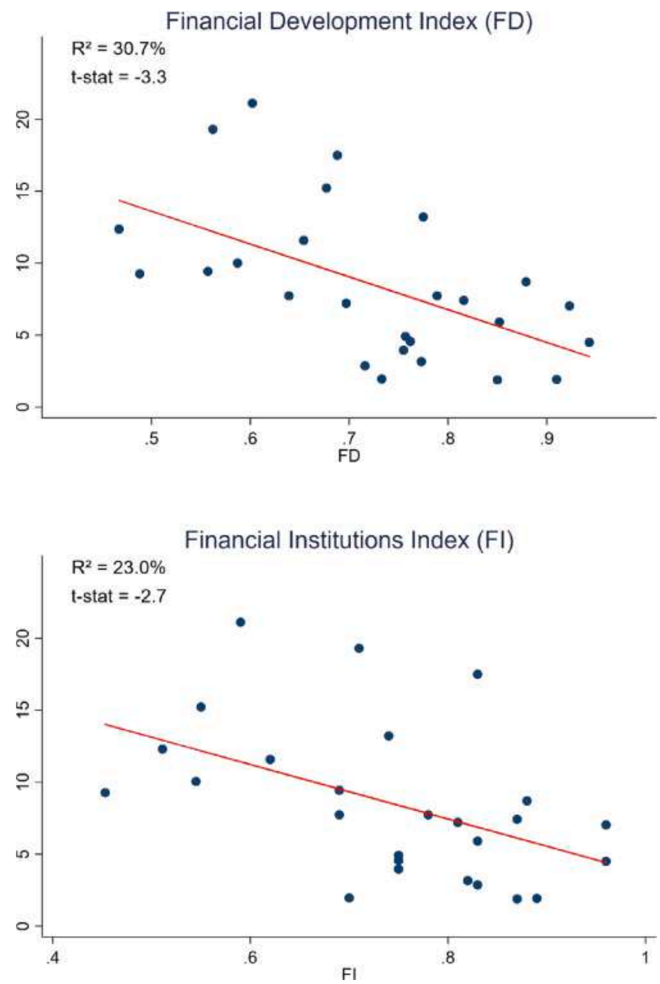


Fig. 4. Financial Development Index and Foreign Investor Responses.
This figure plots each country/area's financial development index (FDI) from IMF against the regression coefficients of $Gvol \times FOR \times Logsize$ in equation (Eq. (10)). FDI index is a relative ranking of countries on the depth, access, and efficiency of their financial institutions and financial markets. The financial institutions Index (FII) is a component of FDI that measures domestic institutions depth (including banks, pension funds, mutual funds, and insurance sector), access and efficiency. The regression is done for each individual developed economy and emerging market groups (Americas, Europe, and Asia-Pacific).

funds, insurance companies, and commercial banks. Within the *Active Investors* group, we further split our sample according to investor skill and assets under management. *High-Skill Investors* are investors whose past one-year portfolio return is above the sample median and *Low-Skill Investors* are those whose return is below the median value. Finally, we argue that funds that are larger are more likely to have greater information capacity. We define two sets of investors: *Large Investors* are those whose average AUM in a given year-quarter is above the sample AUM median, *Small Investors* are those whose AUM is equal to or below the median value.

With these measures of sophistication, we estimate our model in Eq. (10) using specifications (3) (columns 1 and 3) and (4) (columns 2 and 4), defined above. The results are reported in Table 8. In Panel A, we consider the measure of activeness. For the two groups of investors, we observe a strong positive effect of volatility on portfolio flows of domestic and foreign investors, with foreign investors having a stronger effect for the group of active investors. A similar specification for passive investors uncovers a slightly weaker relationship. Further, the effect of volatility on foreign investors is not different from that on domestic investors. The difference between active and passive investors still holds once we apply specification (4). The results are qualitatively similar, and if anything quantitatively stronger, when we use different definitions of sophistication, in Panel B and C. The heterogeneity is particularly visible for the subset of high-skill and low-skill investors. We conclude that investors' response to global volatility shocks depends to a large extent on the level of their information capacity, which is consistent with the information-based mechanism we posit.

Investor sophistication: developed vs. emerging markets. In yet another test of our model, we explore the heterogeneity in portfolio flows between investors in firms located in developed vs. emerging markets. Given our previous findings, we only zoom in on investors with high information capacity. We present the results in Table 9, in Panel A for developed markets, and in Panel B for emerging markets. Consistent with our previous findings, we find that in response to the shock in global volatility, sophisticated investors in developed markets exhibit preference for companies with larger market capitalization. This preference is present for both domestic and foreign investors, even though the latter effect is economically stronger. The results change somewhat for the sample of firms in emerging markets. We observe that the preference for large-cap stocks is mostly present among foreign investors. Not only are the effects for this sample strong but also they are economically larger than those for the sample of firms in developed markets. Overall, the results underscore the importance of filtering out information-insensitive components of flows and the role of asymmetric information for the economic magnitude of the reallocation process.

Investor sophistication: the impact on sample compositions. As a final test of our model, we study the role of entry and exit of investors into asset markets. The motivation for this analysis stems from the observation we made in Section 3: When we disaggregate the data from firm level to firm-investor level, we observe that the average sensitivity of fund flows to external shocks goes significantly higher. To understand this result, it is useful to link this result to the predictions of our theoretical model. We showed so far that sophisticated investors in our data are more sensitive to the global shock and reallocate their portfolios from small to large companies. Given this result, one could argue that the disaggregation effect are driven by entry of investors with higher flow sensitivity and exit of investors with lower sensitivity. We explore this prediction using a refined version of our specification in Eq. (10). Formally, we estimate the following two regression models:

$$
\begin{aligned}
Exit_{i,j,t} &= g_0 + g_1\{Gvol_t,\ Active_{i,j},\ Logsize_{i,t-1}\} \\
&\quad + g_2\text{Controls}_{i,t-1} + \mu_{i,j} + \delta_{i,t} + \epsilon_{i,j,t} \\
Entry_{i,j,t} &= g_0 + g_1\{Gvol_t,\ Active_{i,j},\ Logsize_{i,t-1}\} \\
&\quad + g_2\text{Controls}_{i,t-1} + \mu_{i,j} + \delta_{i,t} + \epsilon_{i,j,t}
\end{aligned}
$$

where $Exit$ is an indicator variable equal to one if the holding position of institution j of stock i at time t is zero and the same position was positive at period $t-1$, $Entry$ is an indicator variable equal to one if the holding position of an institution j of stock i at time t is positive and the same position was zero at period $t-1$. $Active$ is a generic indicator variable, equal to one for investors that are more sophisticated, as per our definitions in Table 8. All other variables are specified as before. We present the results from estimating the regressions in Table 10. Columns 1, 3, and 5 focus on exit decisions, while columns 2, 4, and 6 relate to the entry decision. For our most robust specification, in columns 1 and 2, using the distinction between *Active* and *Passive investors*, we find that sophisticated investors are more likely to exit small companies and less likely to exit large companies when $Gvol$ is higher. Similarly, we observe that *Active investors* are more likely to enter positions in large stocks and less likely positions in small stocks, when $Gvol$ is higher. The results are qualitatively similar when we focus on the distinction between *High-Skill and Low-Skill investors*, although they are weaker quantitatively. Finally, size of assets under management is the weakest among all the sophistication measures. Overall, we find

Table 7
Global volatility and capital flows: Regional markets.
This table presents the investor-firm-level regression results for the relation between global volatility and institutional ownership changes in different regional markets based on a sample of firms between 2000 and 2020. Panel A considers firms located in developed markets and Panel B firms in emerging markets. The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variables are global index volatility ($Gvol$) and foreign institution indicator FOR, and their interaction terms with firm size ($Logsize$) and stock return volatility (Vol). Control variables are the same as those in Table 4. Regression models also include firm×investor and investor × quarter fixed effects, in columns, 1, 3, and 5; and additionally firm × quarter fixed effects, in columns 2, 4, and 6. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Developed						
	Americas		Europe		Asia Pacific	
	$\Delta Log(IO)_{i,j,t}$					
$Gvol_t \times Logsize_{i,t-1}$	7.137***		5.769***		4.963***	
	(2.571)		(1.805)		(1.582)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	2.831***	2.580**	4.534***	7.732***	3.276	6.443**
	(1.017)	(1.195)	(1.451)	(1.703)	(2.546)	(2.791)
Observations	71,546,213	71,546,213	21,033,172	21,033,172	14,132,318	14,132,318
R^2	0.168	0.208	0.167	0.22	0.203	0.265
Panel B: Emerging						
	(1)	(2)	(3)	(4)	(5)	(6)
	Americas		Europe		Asia Pacific	
	$\Delta Log(IO)_{i,j,t}$					
$Gvol_t \times Logsize_{i,t-1}$	−5.821*		3.604		1.539*	
	(3.152)		(3.688)		(0.899)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	13.290***	12.368***	9.304***	9.264**	8.258**	10.010*
	(3.178)	(4.237)	(3.232)	(4.163)	(3.971)	(5.366)
Observations	1,517,356	1,517,356	1,458,089	1,458,089	6,109,623	6,109,623
R^2	0.319	0.374	0.285	0.359	0.202	0.286
Controls and Other Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Quarter FE		Yes		Yes		Yes

some evidence that the lower sensitivity of investor flows to global shocks at the firm level could reflect significant composition effects due to investors endogenously selecting to different stocks in different volatility regimes.

Additional robustness checks. In Appendix C, we provide additional robustness checks for our empirical findings across specifications 1-4. In Table C.6, we exclude U.S investors from the data. In Table C.5 we exclude firms (Panel A) or investors (Panel B) domiciled in tax havens. In Table C.7, we use a change in ownership ($IO_t - IO_{t-1}$) as the outcome variable. Across all the tests, the results remain qualitatively and quantitatively similar. Finally, we explore the effect of different clustering methods in Table C.8. Different clustering assumptions preserve the significance of our estimates.

4.4. Empirical identification

Our results so far indicate strong support for the information-based economic mechanism driving institutional investors' portfolio holdings responses to global volatility. This interpretation is corroborated both by our theoretical model as well as a set of empirical results predicated by the underlying mechanism. The above results clearly point out to a specific mechanism but they do not necessarily provide precise answers to all challenges behind their empirical identification. In particular, one may still worry about potential issues related to endogeneity concerns due to omitted variables or reverse causality. Our use of high granularity data, combined with a high-dimensional set of fixed effects makes it unlikely that our results can be attributed to an unspecified omitted variable. In particular, such a variable would have to vary at the institutional-firm-time level and not purely at firm-time, investor-time, or investor-firm level, since these dimensions of variability are already absorbed by our fixed effects. As is the case in any empirical study, we cannot fully disprove the existence of such omitted variable, however, we can enhance the robustness of our findings through a number of additional identification techniques.

In this section, we provide two sets of empirical tests to allay such concerns. Our first set of results utilizes alternative measures of global volatility that are either less reliant on measures of stock returns, are forward-looking, or rely on the lead–lag structure. Our second set of results takes advantage of two plausibly exogenous shocks to global volatility: granular instrumental variable in the spirit of Gabaix and Koijen (2024) and U.S. monetary policy shock of Rey (2013), Nakamura and Steinsson (2018), Miranda-Agrippino and Rey (2020). The overall conclusions from these different tests indicate that our baseline results are unlikely to be materially affected by endogeneity.

4.4.1. Using alternative measures of market stress

In our first set of tests, we replace our measure of global uncertainty ($Gvol$) with our alternative measures. For each of the measures, we estimate the model in Eq. (10) and present the results in Table 11. In columns 1 and 3, we present the results for specification (3), while in columns 2 and 4, we report results from estimating specification (4). In Panel A, we use the 2008–2009 global financial crisis and the Covid-19 shock as measures of increased uncertainty. Specifically, we define an indicator variable, *Crisis Indicator*, equal to one for all quarters in our data in which the crisis was present (2008Q3–2009Q1 and 2020Q1), and zero otherwise. The advantage of using crisis episodes is their robustness to a potential reverse causality concern whereby investor flows could influence global equity return volatility but are unlikely

Table 8
Global volatility and capital flows: Heterogeneous investors.
Each quarter, we classify investors into active vs. passive (Panel A), and high-skill vs. low-skill (Panel B), and large vs. small (Panel C). The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variables are global equity return volatility ($Gvol$) and foreign institution indicator FOR, and their interaction terms with firm size ($Logsize$) and stock return volatility (Vol). *Active Investors* include active investment advisors and hedge funds; and *Passive Investors* are passive investment advisors, pension funds, insurance companies, and commercial banks. *High-Skill Investors* are investors whose past one-year portfolio return is above the sample median and *Low-Skill Investors* are those whose return is below the median value. *Large Investors* are defined as those whose AUM in a most recent quarter is above the sample median of all firm-institution observations, *Small Investors* are those whose AUM is equal to or below that value. Control variables are the same as those in Table 4. Regression models include firm×investor and investor × quarter fixed-effects, in columns 1 and 3, and firm×investor, firm × quarter, and investor × quarter fixed effects, in columns 2 and 4. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Investor Activeness				
	Active Investors		Passive Investors	
	(1)	(2)	(3)	(4)
	$\Delta Log(IO)_{i,j,t}$		$\Delta Log(IO)_{i,j,t}$	
$Gvol_t \times Logsize_{i,t-1}$	7.385***		2.492	
	(2.531)		(1.658)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	4.011***	4.997***	1.659	3.179
	(1.168)	(1.315)	(1.572)	(1.934)
Observations	102,349,434	102,349,434	14,256,303	14,256,303
R^2	0.136	0.189	0.176	0.327
Panel B: Investor Skill				
	High-Skill Investors		Low-Skill Investors	
$Gvol_t \times Logsize_{i,t-1}$	10.352***		1.086	
	(1.708)		(2.561)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	5.439***	7.987***	−0.244	1.116
	(1.676)	(1.975)	(2.118)	(2.253)
Observations	54,879,641	54,879,641	60,726,096	60,726,096
R^2	0.222	0.281	0.274	0.323
Panel C: Investor Size				
	Large Investors		Small Investors	
$Gvol_t \times Logsize_{i,t-1}$	6.630***		7.505**	
	(2.306)		(3.032)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	3.581***	4.528***	2.173	1.833
	(1.109)	(1.271)	(1.707)	(1.692)
Observations	99,251,922	99,251,922	17,353,815	17,353,815
R^2	0.125	0.181	0.310	0.392
Controls and Other Interactions	Yes	Yes	Yes	Yes
Firm × Investor FE	Yes	Yes	Yes	Yes
Investor × Quarter FE	Yes	Yes	Yes	Yes
Firm × Quarter FE		Yes		Yes

to drive major crises. Our findings, in column 1, reveal a similar positive and statistically significant effect on the discretionary flows to stocks with larger market caps, both domestic and foreign. This finding suggests that during periods of extreme stress, informed institutional investors differentiate among the stocks they buy and sell as they internalize their information advantages. The sensitivity to the global shock increases slightly for foreign stocks when we consider specification (4), as presented in column 2.[17] We conclude that investors' portfolio choices are not simply driven by a desire for uniform scaling down of all holdings, but instead likely reflect an information-driven tradeoff in learning in response to the global shock.

In Panel B, we report the results in which $Gvol$ is replaced by the Financial Uncertainty Index (FUI) of Jurado et al. (2015). The advantage of using this measure is its relative insulation from market/trading activity. We again find results that are consistent with our earlier findings. In times of higher realizations of FUI, investors tend to reallocate their holdings towards larger-cap stocks away from smaller-cap stocks. Notably, the economic magnitude of this reallocation is significantly smaller relative to the one we associated with periods of crisis, further underscoring the importance of extreme periods of stress. In Panel C, we consider the measure of U.S. implied volatility index (VIX). The advantage of this measure is its forward-looking aspect, which makes it less likely that the identified effect is forecastable by measures of past and contemporaneous fundamental information. As a final test, in Panel D, we consider a global volatility measure that is lagged one quarter, thereby making it less likely that it is driven by future value of portfolio flows. We find that our results are quite similar whether we use contemporaneous or a lagged measure of volatility. Overall, the results based on the four different measures of uncertainty paint a very similar picture to those we report in our regressions based on $Gvol$, which makes it unlikely that the results are subject

[17] The impact of crisis episodes on flows is more pronounced in the sample of firms from emerging markets, consistent with the prevalent macro view that global stress affects emerging economies more substantially (Calvo et al., 1996; Rothenberg and Warnock, 2011).

Table 9
Heterogeneous investors in developed and emerging markets.
Each quarter, we classify investors as active, high skill, and large (as in Table 8). Panel A considers investors in developed markets and Panel B in emerging markets. The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variables are global equity return volatility ($Gvol$) and foreign institution indicator FOR, and their interaction terms with firm size ($Logsize$). Control variables, omitted for brevity, are the same as those in Table 4. Regression models additionally include firm×investor and investor × quarter fixed effects, in columns 1, 3, and 5; and firm×investor, investor × quarter, and firm × quarter fixed effects, in columns 2, 4, and 6. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Active		High-Skill		Large	
	$\Delta Log(IO)_{i,j,t}$					
Panel A: Developed						
$Gvol_t \times Logsize_{i,t-1}$	7.495***		10.486***		6.670***	
	(2.556)		(1.736)		(2.304)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	3.912***	4.892***	5.524***	7.778***	3.576***	4.476***
	(1.038)	(1.240)	(1.813)	(2.076)	(0.981)	(1.204)
Observations	94,033,509	94,033,509	50,825,766	50,825,766	90,597,066	90,597,066
R^2	0.142	0.190	0.227	0.281	0.130	0.182
Panel B: Emerging						
$Gvol_t \times Logsize_{i,t-1}$	1.057		1.207		0.381	
	(1.828)		(1.656)		(1.513)	
$Gvol_t \times FOR_{i,j} \times Logsize_{i,t-1}$	10.778***	12.596**	13.673***	14.771***	10.235***	10.404**
	(2.883)	(4.903)	(2.407)	(5.039)	(2.883)	(4.690)
Observations	8,315,925	8,315,925	5,053,875	5,053,875	8,654,856	8,654,856
R^2	0.193	0.278	0.271	0.362	0.178	0.264
Controls and Other Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Quarter FE		Yes		Yes		Yes

Table 10
Exit and entry: Heterogeneous investors.
This table presents the investor-firm level regression results for the relation between global volatility and investor exit and entry decisions into individual assets based on a sample of firms observed between 2000 and 2020. The dependent variable $Exit_{i,j,t}$ is equal to one if institution j's $holding_{i,t-1} > 0$, $holding_t = 0$, and zero otherwise. The dependent variable is $Entry_{i,j,t}$, equal to one if institution j's $holding_{i,t-1} = 0$, $holding_t > 0$, and zero otherwise. The main independent variables are global index volatility ($Gvol$), investor indicator ($Active$, $HighSkill$, $LargeAUM$), and their interaction terms with firm size ($Logsize$). $Active$ is equal to one if investor is active one, and zero otherwise. Active Investors is a subset of investors which includes active investment advisors and hedge funds; Passive Investors are passive investment advisors, pension funds, insurance companies, and commercial banks. $HighSkill$ is equal to one if an investor's past one-year portfolio return is above the sample median, and zero otherwise. $LargeAUM$ is equal to one if an investor's AUM in a given year-quarter is above the sample AUM median, and zero otherwise. Control variables are the same as those in Table 4. Regression models include firm×investor and firm × quarter-fixed effects. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Exit	Entry	Exit	Entry	Exit	Entry
$Gvol_t \times Active$	0.508	−0.153				
	(0.313)	(0.110)				
$Gvol_t \times Active \times Logsize_{i,t-1}$	−0.248**	0.049**				
	(0.099)	(0.021)				
$Gvol_t \times HighSkill$			0.530*	−0.017		
			(0.291)	(0.229)		
$Gvol_t \times HighSkill \times Logsize_{i,t-1}$			−0.091	0.043		
			(0.083)	(0.064)		
$Gvol_t \times LargeAUM$					−1.030*	0.050
					(0.558)	(0.203)
$Gvol_t \times LargeAUM \times Logsize_{i,t-1}$					0.073	0.004
					(0.111)	(0.033)
Controls and Other Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,605,737	116,605,737	116,605,737	116,605,737	116,605,737	116,605,737
R^2	0.195	0.103	0.195	0.103	0.195	0.103

Table 11
Global volatility and capital flows: Alternative uncertainty measures.
The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variables are uncertainty measures ($Uncertainty$) and foreign institution indicator FOR, and their interaction terms with firm size ($Logsize$) and stock return volatility (Vol). We consider four uncertainty measures: Financial Crisis Indicator in Panel A; Financial Uncertainty Index (*FUI*) of Jurado et al. (2015) in Panel B; U.S. implied volatility index (VIX) in Panel C; and one-quarter lagged global equity return volatility ($Gvol$) in Panel D. Control variables are the same as those in Table 4. Regression models additionally include firm×investor, and investor × quarter fixed effects, in columns 1 and 3; and firm×investor, firm × quarter, and investor × quarter fixed effects, in columns 2 and 4. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Crisis Indicator		**Panel B: FUI**	
	(1)	(2)	(3)	(4)
	$\Delta Log(IO)_{i,j,t}$		$\Delta Log(IO)_{i,j,t}$	
$Uncertainty_t \times Logsize_{i,t-1}$	0.170***		0.034**	
	(0.057)		(0.014)	
$Uncertainty_t \times FOR_{i,j} \times Logsize_{i,t-1}$	0.067**	0.081***	0.028***	0.031***
	(0.026)	(0.030)	(0.010)	(0.010)
Observations	116,605,737	116,605,737	116,605,737	116,605,737
R^2	0.139	0.191	0.139	0.191
	Panel C: VIX		**Panel D: Lagged Gvol**	
	(1)	(2)	(3)	(4)
$Uncertainty_t \times Logsize_{i,t-1}$	0.328*		0.927	
	(0.179)		(2.476)	
$Uncertainty_t \times FOR_{i,j} \times Logsize_{i,t-1}$	0.220**	0.276***	2.834*	4.425**
	(0.095)	(0.097)	(1.639)	(1.835)
Observations	116,605,737	116,605,737	116,043,950	116,043,950
R^2	0.139	0.191	0.138	0.190
Controls and Other Interactions	Yes	Yes	Yes	Yes
Firm × Investor FE	Yes	Yes	Yes	Yes
Investor × Quarter FE	Yes	Yes	Yes	Yes
Firm × Quarter FE		Yes		Yes

to a potential reverse causality concern or are spuriously driven by a specific choice of our volatility measure.

4.4.2. Evidence from instrumental variables estimation

An alternative and more direct way to obtain a well-identified set of parameters can be through the use of instrumental variables. While finding a truly exogenous instrument is generally difficult, we can rely on past literature in international finance that offers some useful guidance. Specifically, we follow two commonly used approaches: the Granular Instrumental Variables (GIV) of Gabaix and Koijen (2024) and the U.S. monetary policy and global financial cycles of Rey (2013), Nakamura and Steinsson (2018), Miranda-Agrippino and Rey (2020). In what follows, we discuss how each of the two approaches can be utilized in the context of our empirical tests and discuss in detail the validity of our instruments and empirical estimates of our baseline model.

Granular instrumental variables (GIV) approach. Our first instrument is motivated by the literature on the granular origin of macroeconomic shocks (Gabaix, 2011). In the granular framework, shocks to large and non-atomistic agents generate non-diversifiable "grains" of economic and financial activity, which then affect aggregate fluctuations and all other agents via general equilibrium effects. In this spirit, one can define an instrument as a variable that extracts the idiosyncratic component of large firms relative to the average value of all firms. Indeed, idiosyncratic shocks originating from individual firms are less likely to be caused by common factors (or by omitted variables correlated with those factors) since any such factor would systematically affect all firms. Because our model aims to predict trading activity of investors, we refine our instrument to base it on firm-level idiosyncratic liquidity (turnover ratio) net of its common liquidity component (equal-weighted):[18]

$$GIV_t = \sum_{i=1}^{N} w_{i,t} \times Turnover_{i,t} - \sum_{i=1}^{N} \frac{Turnover_{i,t}}{N}, \tag{11}$$

where N is the total number of firms in sample for each quarter, $w_{i,t}$ is the weight of firm size over whole market capitalization in each quarter. This instrument clearly satisfies the relevance condition and quite plausibly the exclusion restriction. Empirically, as both the global stock volatility and our instrument are cross-sectionally invariant, their values are common for all firms within each time period. This means that the usual two-stage least-squares regression is not appropriate in this context, since it would mechanically overstate the correlation between the endogenous variable and instrument variable. To address this concern, we follow Gulen and Ion (2015) and estimate a time-series regression in the first stage and a panel regression with fitted volatility in the second stage.[19] Specifically, the first-stage regression takes the following form:

$$Gvol_t = a_0 + a_1 GIV_t + a_2 Controls_t + \epsilon_t \tag{12}$$

$Controls_t$ is a vector of time-varying firm variables including the average levels of firm size, firm volatility, book-to-market ratio, leverage,

[18] Instead of constructing GIV at the firm level, we can build the GIV using investor level, or investor-firm level data. Firm's idiosyncratic volatility can also be used to construct GIV. The results are quantitatively and qualitatively similar.

[19] For robustness check, we also conduct the usual two-stage least-squares regression (2SLS) in Table C.9 of the Appendix. Besides, we also bootstrap the standard errors as in Gulen and Ion (2015) for the firm-level analysis and find that the standard errors are close to those from clustering at quarter and economy levels.

Table 12

Global volatility and capital flows: Instrumental variables approach.

The dependent variable is the change of the natural logarithm of ownership $\Delta Log(IO)$. The main independent variable is global index volatility ($Gvol$) instrumented in two ways. In Panel A, our instrument is a granular instrumental variable (GIV) calculated as the difference between firm size-weighted turnover ratio and equal-weighted turnover ratio across all firms at each time point. In Panel B, our instrument is based on the U.S. monetary policy news shock of Nakamura and Steinsson (2018). We use absolute levels of the monetary policy news shocks. The main independent variables are $Gvol$ and foreign institution indicator FOR, and their interaction terms with firm size ($Logsize$) and stock return volatility (Vol). Control variables, omitted for brevity, are the same as those in Table 4. In the first stage, we estimate a time-series regression, as in Eq. (12). In the second stage, we estimate a regression model in an investor-firm-level sample using the fitted values of $Gvol$ from the first stage. Regression models additionally include firm×investor, and investor × quarter fixed effects, in column 2; and firm×investor, firm × quarter, and investor × quarter fixed effects, in column 3. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: GIV			
	(1)	(2)	(3)
	First Stage	Second Stage	
	$Gvol_t$	$\Delta Log(IO)_{i,j,t}$	
GIV	0.094***		
	(0.012)		
$\widehat{Gvol}_t \times Logsize_{i,t-1}$		6.679**	
		(3.138)	
$\widehat{Gvol}_t \times FOR_{i,j} \times Logsize_{i,t-1}$		4.869**	6.560***
		(2.184)	(2.210)
Observations	80	116,605,737	116,605,737
R^2	0.677	0.139	0.191
Panel B: US MPS			
	First Stage	Second Stage	
	$Gvol_t$	$\Delta Log(IO)_{i,j,t}$	
MPS	0.094**		
	(0.036)		
$\widehat{Gvol_t^{mps}} \times Logsize_{i,t-1}$		7.831*	
		(4.005)	
$\widehat{Gvol_t^{mps}} \times FOR_{i,j} \times Logsize_{i,t-1}$		4.967*	7.089**
		(2.782)	(2.742)
Observations	80	116,605,737	116,605,737
R^2	0.458	0.139	0.191
Controls and Other Interactions	Yes	Yes	Yes
Firm × Investor FE		Yes	Yes
Investor × Quarter FE		Yes	Yes
Firm × Quarter FE			Yes

turnover and profitability. We report the results from the estimation in Panel A of Table 12. Column 1 provides the estimates for the first-stage equation. The F-statistic for the GIV coefficient is larger than 20, implying the strength of our instrument. In columns 2–3, we estimate the average effect of global volatility on investor-firm-level capital flows using the fitted values from Eq. (12) to capture the exogenous variation in global stock volatility and a set of different fixed effects as before. Similar to the results in Table 6, we again find a strong positive reallocation effect of investors towards larger firms. The magnitudes of the effects are slightly larger than the estimates reported before, thus suggesting a possibility of downward bias in the original estimates.

We provide additional robustness to the GIV framework using the following four robustness tests. First, if a large idiosyncratic shock coincides with a large aggregate event, the standard model estimates could lead to bias. Following Gabaix and Koijen (2024), we conduct a narrative check and remove these important event periods (mainly GFC and COVID periods). Second, as the regression samples also include large firms, we remove the top 10% largest firms (accounting for more than 80% of the total market capitalization) from the sample and re-estimate our baseline regressions. Third, we construct two GIVs based on two types of entities, developed and emerging countries, and form the GIVs based on the size-weighted sum of idiosyncratic shocks of each type (i.e., with two different sets of weights). Finally, we present additional results from usual two-stage least-squares regression (2SLS). The results from these estimation experiments are presented in Table C.9 of the Appendix, showing that they remain similar across all specifications.

U.S. monetary policy shock. To complement the GIV approach, we apply the second instrument based on U.S. monetary policy shocks (MPS). This instrument is motivated by the observation that U.S. MPS strongly induce co-movements in the international financial variables that characterize the "Global Financial Cycle" (Rey, 2013; Miranda-Agrippino and Rey, 2020). Such policy shocks could significantly affect global asset price dynamics and thus satisfy the relevance condition.

One challenge for the validity of this instrument is that monetary policy changes happen for a reason; for instance, the central bank might lower interest rates to counteract the effects of a negative shock to the economy and financial sector. To extract the exogenous component of U.S. MPS, we follow the high-frequency identification approach of Nakamura and Steinsson (2018), and Acosta (2023) and use the "policy news shock", calculated as the unexpected change of interest rates in a 30 min window surrounding scheduled Federal Reserve announcements. The unexpected changes of interest rates in these very narrow windows are unlikely to be induced by global volatility and firm capital flows. Further, since multiple shocks may occur in a given quarter, our quarterly MPS weighs equally all monthly MPS.

Our key exclusion restriction is that the monetary policy shocks affect firm-level capital flows only through the market uncertainty (global volatility) channel but not through other ways. The estimated "policy news shocks" are quite small (a standard deviation of only about 5 basis points) and this precludes direct estimation of their effect on real activity (Nakamura and Steinsson, 2018). In unreported tables, we confirm that the level of policy news shocks do not directly influence the firm-level and investor-firm level capital flows in international firms. In the empirical analysis, instead of using the level of policy news shock, we use the absolute value of the level of policy news shock as the instrument for market uncertainty, and thus for global market volatility (IV MPS). The uncertainty of the policy news shock is a proper instrument that carries a significant relationship with global market volatility and affects micro-level capital flows only through this relationship.

Similar to Eq. (12), we estimate a time-series regression in the first stage and a panel regression with the fitted value of $Gvol$ in the second stage. We present the results in Panel B of Table 12. In columns 2–3, we show the coefficients from estimating the average effect of global volatility on discretionary flows using the fitted values from the first-stage regression. Like before, we consider specifications (3) and (4). The results broadly corroborate those in Panel A: institutional investors tend to reallocate their capital towards larger companies. The magnitudes of the effects are slightly larger than those from GIV regressions but not by a lot, which supports our earlier conjecture that the endogeneity issues are not of first-order importance in our setting.

5. Implications for financial stability

In this section, we study the implications of our results for financial stability. In particular, we study the role of the changing ownership structure for future firm-level stock return volatility and stock turnover, measured as trading volume over the number of shares outstanding. We associate greater (smaller) firm-level volatility (turnover) with more instability in the market. We estimate the following regression model:

$$\begin{aligned} Stability_{i,t+1} &= j_0 + j_1\{log(Hold_{i,t}/Hold_{i,t-1}),\ Gvol_t,\ Logsize_{i,t-1}\} \\ &\quad + j_2\text{Firm Controls}_{i,t-1} + \mu_i + \delta_{c,t} + \epsilon_{i,t} \end{aligned} \tag{13}$$

Table 13
Institutional flows and future firm stability.
This table presents the firm-level regression results for relation between the institutional ownership changes and future stock stability (volatility and liquidity) based on a sample of firms between 2000 and 2020. We report the results for the full sample, as well as for developed and emerging markets sub-samples. Panel A reports the results for firm volatility, and Panel B reports the results for firm liquidity, measured by stock turnover ratio. The dependent variables are the stock return volatility in next quarter $Vol_{i,t+1}$ for Panel A, and liquidity in next quarter $Turnover_{i,t+1}$ for Panel B. The main independent variables are $\Delta Log(IOFOR)$, $\Delta Log(IODOM)$, $\Delta Log(IO)$, and their interaction terms with global index volatility ($Gvol$) and firm size. Control variables include firm characteristics ($Logsize$, Vol, $Turnover$, $Leverage$, BM, $PRratio$). The data section provides detailed definitions of these variables. All regression models include firm and economy × quarter fixed effects. Robust standard errors, double clustered at the firm and quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firm Volatility

	ALL						Developed						Emerging					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16	(17)	(18)
	$Vol_{i,t+1}$						$Vol_{i,t+1}$						$Vol_{i,t+1}$					
$\Delta Log(IOFOR)_{i,t}$	−0.055***	0.054***	0.060***	0.034***	0.081***	0.074***	−0.061***	0.062***	0.062***	0.028**	0.091***	0.078***	−0.026**	0.016	0.033*	−0.020	−0.022	−0.004
	(0.010)	(0.016)	(0.016)	(0.011)	(0.021)	(0.021)	(0.011)	(0.019)	(0.019)	(0.012)	(0.022)	(0.022)	(0.011)	(0.020)	(0.018)	(0.012)	(0.030)	(0.032)
$\Delta Log(IODOM)_{i,t}$	−0.194***	−0.033	−0.026*				−0.268***	−0.057**	−0.028				0.000	0.040***	0.040***			
	(0.013)	(0.023)	(0.014)				(0.017)	(0.026)	(0.019)				(0.009)	(0.014)	(0.014)			
$\Delta Log(IO)_{i,t}$				−0.215***	−0.069**	−0.029				−0.284***	−0.094***	−0.032				−0.007	0.048**	0.045
				(0.014)	(0.028)	(0.024)				(0.017)	(0.031)	(0.026)				(0.011)	(0.024)	(0.031)
$\Delta Log(IOFOR)_{i,t} \times Gvol_t$		−12.758***	−11.599***		−5.451**	−6.605***		−14.404***	−12.233***		−7.404***	−6.848***		−4.980***	−6.263***		0.209	−2.602
		(1.412)	(1.442)		(2.351)	(2.376)		(1.732)	(1.886)		(2.334)	(2.464)		(1.678)	(1.440)		(3.369)	(3.791)
$\Delta Log(IODOM)_{i,t} \times Gvol_t$		−18.792***	−13.199***					−24.591***	−17.969***					−4.640***	−4.686***			
		(2.608)	(1.279)					(2.854)	(1.934)					(1.489)	(1.338)			
$\Delta Log(IO)_{i,t} \times Gvol_t$					−16.953***	−11.815***					−22.129***	−18.098***					−6.446**	−4.593
					(3.434)	(3.015)					(3.757)	(3.117)					(2.771)	(3.701)
$\Delta Log(IOFOR)_{i,t} \times Gvol_t \times Logsize_{i,t}$			−1.993			−2.859*			−1.087			−1.580			−4.435**			−6.165***
			(1.717)			(1.652)			(1.816)			(1.771)			(1.741)			(2.255)
$\Delta Log(IODOM)_{i,t} \times Gvol_t \times Logsize_{i,t}$			3.270***						1.809						1.632			
			(1.156)						(1.485)						(1.194)			
$\Delta Log(IO)_{i,t} \times Gvol_t \times Logsize_{i,t}$						1.666						−0.095						2.250
						(1.224)						(1.414)						(2.481)
Controls and Other Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economy × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,259,103	1,259,103	1,259,103	1,258,641	1,258,641	1,258,641	973,045	973,045	973,045	972,611	972,611	972,611	286,058	286,058	286,058	286,030	286,030	286,030
R^2	0.776	0.776	0.776	0.776	0.776	0.776	0.782	0.782	0.783	0.782	0.782	0.783	0.553	0.553	0.553	0.553	0.553	0.553

Panel B: Firm Liquidity

	ALL						Developed						Emerging					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16	(17)	(18)
	$Turnover_{i,t+1}$						$Turnover_{i,t+1}$						$Turnover_{i,t+1}$					
$\Delta Log(IOFOR)_{i,t}$	0.015***	0.023***	0.027***	0.014***	0.021***	0.025***	0.022***	0.026***	0.031***	0.021***	0.025***	0.030***	−0.007*	0.013**	0.012**	−0.031***	−0.009	−0.009
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.009)	(0.010)
$\Delta Log(IODOM)_{i,t}$	0.020***	0.022***	0.024***				0.013***	0.016***	0.018***				0.035***	0.035***	0.038***			
	(0.002)	(0.003)	(0.003)				(0.002)	(0.005)	(0.005)				(0.004)	(0.007)	(0.008)			
$\Delta Log(IO)_{i,t}$				0.006***	0.007***	0.006				0.004*	0.005	0.005				0.031***	0.028***	0.028**
				(0.002)	(0.003)	(0.004)				(0.002)	(0.004)	(0.005)				(0.004)	(0.011)	(0.013)
$\Delta Log(IOFOR)_{i,t} \times Gvol_t$		−0.909**	−1.165***		−0.832**	−1.026**		−0.537	−0.807*		−0.511	−0.696**		−2.240***	−2.361***		−2.613**	−3.010**
		(0.405)	(0.332)		(0.409)	(0.428)		(0.480)	(0.422)		(0.375)	(0.329)		(0.480)	(0.447)		(1.024)	(1.188)
$\Delta Log(IODOM)_{i,t} \times Gvol_t$		−0.207	−0.447					−0.315	−0.528					−0.074	−0.247			
		(0.352)	(0.332)					(0.677)	(0.645)					(0.717)	(0.797)			
$\Delta Log(IO)_{i,t} \times Gvol_t$					−0.205	−0.339					−0.120	−0.348					0.351	0.646
					(0.217)	(0.378)					(0.467)	(0.606)					(1.246)	(1.563)
$\Delta Log(IOFOR)_{i,t} \times Gvol_t \times Logsize_{i,t}$			0.021			−0.096			0.051			−0.038			−0.040			−0.597
			(0.195)			(0.190)			(0.173)			(0.191)			(0.413)			(0.432)
$\Delta Log(IODOM)_{i,t} \times Gvol_t \times Logsize_{i,t}$			0.192*						0.234						0.080			
			(0.106)						(0.163)						(0.346)			
$\Delta Log(IO)_{i,t} \times Gvol_t \times Logsize_{i,t}$						0.221						0.189						0.649
						(0.168)						(0.244)						(0.462)
Controls and Other Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economy × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,257,076	1,257,076	1,257,076	1,256,617	1,256,617	1,256,617	971,364	971,364	971,364	970,933	970,933	970,933	285,712	285,712	285,712	285,684	285,684	285,684
R^2	0.658	0.658	0.659	0.658	0.658	0.659	0.664	0.664	0.665	0.664	0.664	0.665	0.645	0.645	0.646	0.645	0.645	0.645

where $Stability$ is a generic variable for $Volatility$ and $Turnover$, measured one quarter ahead, $Hold$ is a generic variable for foreign, domestic and total ownership, measured at the firm level. $\{log(Hold_{i,t}/Hold_{i,t-1}),\ Gvol_t,\ Logsize_{i,t}\}$ denote the set of all interaction terms between the three variables in curly brackets. Our vector of firm controls includes $Volatility$, $Logsize$, B/M, $Leverage$, $Turnover$, and $Profitability$.

We report the results of the estimation in Table 13. Panel A shows the results for the volatility regression. In column 1, we present the results for the changes in ownership. We find that an increase in both domestic and foreign ownership predicts subsequent decline in firm-level volatility. The result is statistically and economically significant. In columns 2–3, we study this effect conditional on the level of $Gvol$ and $Logsize$. We find that in times of high global volatility institutional investors' increase in ownership is more likely to stabilize firm-level return volatility, especially for larger stocks.

Our earlier results indicate that periods of high volatility typically witness an outflow of capital from stocks, which implies that such periods lead to financial instability via a portfolio retrenchment channel. Intriguingly, this destabilizing force is not symmetric, as large stocks do not actually experience significant outflows of capital; in fact, they may see an increase in flows. In this regard, our results suggest that episodes of high volatility may lead to instability for some stocks (small-cap stocks) while promoting stability for others (large-cap stocks). When controlling for the effect of total ownership, we find that foreign investors can stabilize markets more effectively than domestic investors.

Panel B displays the results for stock turnover. In the sample of firms from all economies, we find that an increase in holdings by either domestic or foreign institutions predicts a subsequent increase in stock turnover, which we interpret as improved liquidity. The effect is asymmetric across periods of high and low global volatility, especially for emerging markets during turbulent times. When we condition the results on the location of firms, we find a similar set of results for the sample of firms in developed markets. Further, when controlling for the effect of total ownership, our findings indicate that foreign investors can enhance liquidity more effectively compared to domestic investors.

6. Concluding remarks

Global portfolio flows play an increasingly important role in the distribution of welfare and financial stability worldwide, as evidenced by recent episodes of market-wide stress. It is thus crucial to understand their drivers in order to discern specific mechanisms driving their distribution and the resulting financial policies. This task becomes challenging when using aggregate country-level flow data, as any empirical evidence may be subject to multiple explanations. This paper aims to characterize the conditional behavior of global portfolio flows using novel micro-level evidence on equity holdings at the firm and investor level. Utilizing more granular data allows us to distinguish among various explanations of flows. We propose one such mechanism, an information-based portfolio choice with heterogeneous investors and assets, and show that such mechanism finds significant support in the portfolio-level data we study. In particular, our model predicts a novel form of flight-to-safety mechanism in which investors with more information capacity reallocate their holdings from assets with smaller size and lower volatility towards assets that are large and more volatile. We find that such channel operates in all markets, but becomes stronger for foreign institutional investors in emerging markets. Our further contribution is to distinguish flows that are driven by external factors from those that mostly depend on discretionary investor decisions. Our results indicate that the discretionary component of fund portfolio decisions is much more sensitive to aggregate shocks thereby suggesting that policies aimed at regulating aggregate flows versus regulating holdings of institutions by type or holdings of specific asset classes can have very different implications for the resulting portfolio reallocation. Specifically, our findings suggest that solely focusing on regulating cross-border capital flows as a whole may be an imprecise policy instrument which can have unintended consequences in terms of rebalancing investment flows across stocks, providing more stability to some firms at the expense of others.

CRediT authorship contribution statement

Marcin Kacperczyk: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Jaromir Nosal:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Tianyu Wang:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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