Correlated Demand Shocks and Asset Pricing*

Byungwook Kim†

December 31, 2022

Abstract

This paper proposes a mechanism through which institutional investors' correlated demand shocks provide a source of risk in asset pricing. Institutional investors have a mandate to beat a similar market index (e.g., S&P 500). When the market index performs well, they have a stronger incentive to perform better to catch up with the market performance. I show that this incentive induces procyclical risk-taking behavior among institutional investors, generating correlated demand that causes stocks to excessively comove with the market. I develop and estimate a model and show that stocks with higher exposure to these correlated demand shocks have higher market betas and risk premia due to their amplified market risk. This endogenous risk commands an 8.52% annual return premium in decile portfolios, which is fully explained by the differences in market betas across the portfolios. Quasi-experiments using exogenous changes in index membership provide causal evidence of the mechanism.

Keywords: Correlated demand shocks, asset pricing, institutional investors
JEL Classification: G11, G12, G23

*I am deeply grateful to Zahi Ben-David, Andrei Gonçalves, Ye Li, René Stulz, and Lu Zhang for their continuous guidance for this project. I thank helpful comments from Justin Birru, Francesco Franzoni, Raife Giovinazzo, Kewei Hou, Mark Huson, Philipp Illeditsch (discussant), Aditya Kaul, Hyeik Kim, Jeong Ho (John) Kim (discussant), Jiacui Li, Victor Lyonnet, Vikas Mehrotra, Rabih Moussawi, Ashish Sahay (discussant), Leandro Sanz, Amin Shams, Christof Stahel, Michael Weber, Michael Weisbach, Michael Wittry, Michael Young (discussant), and participants at The Ohio State University, University of Alberta, 2022 LBS TADC, 2022 NFA, 2022 FMA, and 2022 AFBC.

†Fisher College of Business, The Ohio State University. Email: kim.7336@osu.edu.

1 Introduction

Demand shocks unrelated to fundamentals play no role in textbook asset pricing theory. Underlying the traditional framework is the assumption that demand shocks for an asset are uncorrelated across investors. Specifically, when demand shocks to some investors influence price, many other price-elastic investors immediately and aggressively make opposite trades until the price moves back to the fundamental value. Recent research has challenged this notion and examined the importance of correlated demand shocks in shaping equilibrium asset prices.[1] Importantly, Koijen and Yogo (2019) document that correlated shocks to latent demand, the sources of which econometricians do not observe, explain up to 81% of the cross-sectional variance of stock returns. Despite the economic significance, there is relatively little systematic knowledge of the channels driving correlated demand shocks across different groups of investors. Therefore, more research is needed to broaden the understanding of what determines correlated demand shocks and their effects.

In this paper, I propose a mechanism through which institutional investors' correlated demand shocks, caused by their incentive to beat a similar market index (e.g., the S&P 500), provide a source of risk exposure in the cross-section of stock returns.[2] I show theoretically that when this common incentive affects institutional investors' portfolio choices, their optimal rebalancing generates demand shocks that covary with the direction of market movements, amplifying the market risk of affected stocks. I then develop and estimate a model that incorporates these economic forces. The estimated model shows that stocks with high exposure to these correlated demand shocks have higher market betas and risk premia than stocks with low exposure because of their amplified market risk. This endogenous risk commands an 8.52% annual return premium in decile portfolios, which is quantitatively explained by the differences in market betas across the portfolios. Using exogenous changes in index membership, I present causal evidence on the mechanism.

[1] E.g., Brunnermeier and Pedersen (2009); He and Krishnamurthy (2013); Dou, Kogan, and Wu (2022)

[2] Institutional investors are herein defined as professional asset managers who manage equity portfolios on behalf of households, such as mutual funds.

To start, I empirically show that a large majority of funds (typically more than 60%) underperform the market and increase their equity exposure (by becoming net stock buyers and decreasing their cash holdings) when the market performs well, with the opposite patterns present when the market performs poorly. To understand the underlying mechanism, consider a portfolio manager for an equity fund with flows that chase its performance relative to a given market index (e.g., the Russell 1000).[3] If the manager underperforms the market when the market performs well, then she has an incentive to increase her risk premium through higher market exposure during market upswings. In this case, the manager is a net buyer of stocks during periods of positive market performance. This risk-taking strategy will typically pay off since the market performance is, on average, positive. However, if the market unexpectedly falls, the fund will perform poorly due to its higher equity allocation, and its counterpart, lower cash balance, will force the manager to liquidate her positions to meet outflows. As such, the manager is a net seller of stocks during market downturns.

Overall, these effects suggest that institutional investors' demand for stocks covary with market movements, potentially increasing the market betas of affected stocks. I develop and estimate a stylized model that embodies this endogenous market comovement channel through institutional investors' trading behavior. The purpose of the model is to study the cross-sectional variation in stocks' exposure to institutional investors' correlated demand shocks. In other words, the model asks which stocks are most affected when institutional investors tend to buy (sell) stocks when the market rises (falls).

The model takes the ownership structure and documented equity allocation decisions of institutional investors as given. Specifically, the model assumes that institutional investors tend to increase (decrease) their equity exposure when the market performs well (poorly) for an exogenous reason. This setup is highly stylized but useful because it guides my empirical work in a simple manner. However, I later show that the same economic forces arise endogenously due to institutional investors' incentives to outperform a similar market

[3] In a recent sample, the fraction of funds benchmarked against the broad-market index has decreased (Evans, Gómez, Ma, and Tang, 2022; Mullally and Rossi, 2022).

index, building on the general equilibrium framework of Basak and Pavlova (2013).

In the stylized model, institutional investors choose which stocks to buy or sell within their portfolios, given their equity allocation decisions. They take two factors into account when trading. First, when they increase (decrease) their equity exposure, they tend to increase (decrease) their stock holdings in proportion to the current portfolio weights (Edmans, Goldstein, and Jiang, 2012). Consequently, stocks with high institutional ownership are highly exposed to institutional investors' correlated trading since their portfolio weights tend to be large for institutional investors. Second, institutional investors are potentially concerned about the price impact of their trades since they are large investors. Without this latter concern, total institutional ownership would perfectly capture stocks' exposure to institutional investors' correlated demand shocks. However, the estimated model shows that institutional investors try to minimize their price impact when they make trades, materially altering their trading behavior. Specifically, they tend to reduce the size of their trades when their ownership is large compared to the stock's market value or trading volume. Incorporating this trading behavior, the estimated model generates a measure for a stock's exposure to correlated demand shocks (model-implied exposure), which is the sum of the predicted amount of correlated trades across institutional investors scaled by firm size. Intuitively, the price of a stock is potentially affected by correlated demand shocks when the expected correlated trading pressure is large relative to its market value.

The model-implied exposure further motivates a simple empirical proxy for a stock's exposure to correlated demand shocks: the number of institutional owners, controlling for firm size. The number of institutional owners (NIO) predicts the sum of correlated trades across institutional investors (the numerator in the model-implied exposure) in a simple manner. Intuitively, a large number of owners implies a large and dispersed ownership structure. Because the ownership structure is dispersed, each owner is small compared to the total market value or trading volume. Therefore, each owner is not particularly concerned about the price impact of their trades. However, when demand shocks are correlated across them, the price impact can be large in aggregate because they trade in the same direction without worrying about their price impact from each owner's perspective.[4]

In the main tests, I present two sets of results using the model-implied exposure and NIO. For the latter, I include firm size as a control variable (among others) in regression analyses as guided by the model. For a single sorting variable in portfolio analyses, I construct a variable, Residual NIO, which is the estimated residuals from cross-sectional regressions of NIO on firm size. This simple measure well captures a stock's exposure to correlated demand shocks as predicted by the model.

Armed with proxies of stocks' exposure to correlated demand shocks, I present the main empirical results. My sample period extends from 1980 to 2020. First, I find that stocks' market beta is positively related to the proxies of stocks' exposure to correlated demand shocks, controlling for stock characteristics. For example, a percentile rank increase of 50 for the model-implied exposure or NIO is associated with an increase in a market beta of 0.4. Taking the annualized volatility of the stock market as 15%, this corresponds to a 6-percentage-point increase in systematic volatility. Using disaggregated fund-level data, I find that the relation primarily originates from active rather than passive funds. Other variables, such as the total 13F institutional ownership and its Herfindahl-Hirschman index (HHI), also appear to capture stocks' exposure to correlated demand shocks. Specifically, these variables also predict stocks' market beta in the expected direction. Nevertheless, the model-implied exposure and NIO capture the variation in market betas better than the other variables, as indicated by the estimated model.

One potential concern with my setup is the endogeneity of the proxies for stocks' exposure to correlated demand shocks. For instance, because my measures reflect investors' trading decisions, they may be simply picking up fundamentals. To address this issue, I use the Russell 1000 and 2000 reconstitution events as quasi-natural experiments. These events cause a sharp change in the number of active institutional owners, especially among stocks

[4] Greenwood and Thesmar (2011)'s "fragility" measure is partly related to this argument. They study the implications of both concentrated and dispersed ownership structures.

around the Russell 1000 and 2000 cutoffs.[5] I confirm that the relation between market betas and the number of active funds holds in a fuzzy regression discontinuity setting, supporting a causal interpretation of the findings.

While the Russell 1000 and 2000 reconstitution events do not affect total active ownership (Appel, Gormley, and Keim, 2020), these events do change the number of active owners for exogenous reasons. In particular, many active funds' investment mandates require managers to pick stocks that comprise large-cap indexes such as the Russell 1000.[6] These constraints, unrelated to fundamentals, generate a discontinuity in the number of active funds around the Russell 1000 and 2000 cutoff points following the reconstitution dates.

Finally, I explore the asset pricing implications of the main findings. First, Fama and MacBeth (1973) regressions show that both the model-implied exposure and NIO predict returns, controlling for stock characteristics. The return predictability suggests that stocks' amplified market exposure is a priced source of risk. Portfolio formations based on these measures produce a consistent picture. For example, when forming 10 value-weighted portfolios based on Residual NIO, the monthly returns increase monotonically from the lowest decile portfolio (89 basis points) to the top decile portfolio (160 basis points). Importantly, differential market exposure fully explains the return spread with zero alphas. The market betas increase monotonically from the bottom decile portfolio (0.93) to the top decile portfolio (1.44).

The return predictability of NIO differs from the findings of Chen, Hong, and Stein (2002), who argue that reductions in the number of mutual funds imply overvaluation and thus predict abnormally low returns.[7] Empirically, the return predictability of NIO holds after controlling for Chen et al. (2002)'s measure. More importantly, NIO predicts returns

[5]For implementation, I follow a methodology suggested by Ben-David, Franzoni, and Moussawi (2019), which significantly improves the predictive power of the treatment variable.

[6]For example, the prospectus of the Fidelity Stock Selector Large Cap Value Fund (ticker FSLVX) states, "... normally investing at least 80% of assets in stocks of companies with large market capitalizations (which, for purposes of this fund, are those companies with market capitalizations similar to companies in the Russell 1000 Index or the S&P 500 Index)..."

[7]In particular, reductions in the number of mutual funds mean that only optimists are holding stocks as many pessimists have already exited their positions, finding it difficult to sell short.

due to compensation for risk, while their measure predicts returns due to mispricing. More simply put, my paper is about beta, while their work is about alpha.

I further demonstrate that the return predictability of NIO originates from a covariance channel. Specifically, using the IPCA framework of Kelly, Pruitt, and Su (2019), I show that stocks' exposure to correlated demand shocks predicts returns only through beta, not alpha. The undiversifiable risk materializes in bad times, such as during the global financial crisis in 2008, as stocks with high exposure to correlated demand shocks experience large price crashes due to massive correlated selling pressure from institutional investors.

One may find it difficult to reconcile this paper's findings with the low-risk anomaly literature. In particular, Frazzini and Pedersen (2014) show that high-beta stocks earn abnormally low returns, whereas the top decile portfolios in my analyses have the highest beta and earn the highest return. However, empirical tests can fail to uncover a positive market risk premium even if investors require compensation for market exposure. One reason is that market betas may be correlated with other risk exposures that are omitted from asset pricing tests (Giglio and Xiu, 2021). My work identifies an important driving force for market betas, capturing a component of market exposure that is strongly priced. This driver is less likely to be correlated with other sources of risk exposure.

I explore several alternative explanations for my main findings. One may argue that institutional investors buy (sell) stocks when the market performs well (poorly), not because of their discretionary trading (i.e., risk-taking) but because of flows. In principle, the model I estimate does not take a stand on which channel drives correlated demand, and both channels can play a role. However, I conduct several tests to distinguish between the two and find that flow-induced trading (Coval and Stafford, 2007; Lou, 2012) is not the leading cause of the observed trading behavior for institutional investors. First, I classify active mutual funds into those that receive flows in the same direction as the market and the rest. I find that the results on market betas are stronger for the latter group of funds (i.e., either without flows or with flows that are in the opposite direction of the market), particularly during market upturns. This result may be puzzling at face value because one would not expect low-flow funds to exert strong buying pressure when the market performs well. However, during market upswings, there are no systematic outflows, while funds share a systematic incentive to increase equity exposure. Second, mutual funds decrease their cash holdings and buy more stocks when the market performs well, which is consistent with their incentive to increase equity exposure. Finally, I show that the results are stronger for funds that have underperformed the market, further supporting the risk-taking channel.

One might argue that an "index effect" can explain high market exposure for stocks that join the Russell 1000 (Barberis, Shleifer, and Wurgler, 2005; Greenwood, 2008; Boyer, 2011).[8] This literature predicts that stocks joining the Russell 1000 will exhibit extra comovement with the index (i.e., the stock market) because passive funds that track the index trade Russell 1000 stocks altogether. However, Chang, Hong, and Liskovich (2015) show that index demand is very small for stocks just above the cutoff (joining the Russell 1000) but very large for those just below the cutoff (joining the Russell 2000). The reason for these patterns is that the index weights of the former stocks are minuscule. Empirically, I find no effects from passive funds. Therefore, indexing is unlikely to be the driver of amplified market exposure for the stocks in the Russell 1000.

Contribution and related literature Overall, my work establishes the economic mechanism through which institutional investors' correlated demand shocks arising from their incentive to beat a similar market index give rise to endogenous risk in the cross-section of expected stock returns. I provide robust evidence that the demand shocks channel has a first-order impact on equilibrium asset prices. As such, this paper contributes to a growing literature that studies prices and volatility in financial markets through the lens of demand-based asset pricing theory with institutional investors (e.g., Vayanos, 2004; Brunnermeier and Pedersen, 2009; Dasgupta, Prat, and Verardo, 2011; Vayanos and Woolley, 2013; Basak

[8]Barberis et al. (2005) find that stocks added to the S&P 500 exhibit extra comovement with the index, although Chen, Singal, and Whitelaw (2016) argue that the results are sensitive to specifications.

and Pavlova, 2013; He and Krishnamurthy, 2013; Koch, Ruenzi, and Starks, 2016; Koijen and Yogo, 2019; Cho, 2020; Dou et al., 2022; Han, Roussanov, and Ruan, 2022; Buffa, Vayanos, and Woolley, 2022).

My work also makes a theoretical contribution to the literature examining the asset pricing implications of benchmarking (Brennan, 1993; Cuoco and Kaniel, 2011; Basak and Pavlova, 2013; Kashyap, Kovrijnykh, Li, and Pavlova, 2020; Pavlova and Sikorskaya, 2022; Buffa and Hodor, 2022). My model and empirical results offer new insights into asset price formation in the cross-section of average returns.

This paper is also related to the herding literature (e.g., Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999; Nofsinger and Sias, 1999; Choe, Kho, and Stulz, 1999; Sias, 2004) and contributes to the debate on whether correlated trading of institutional investors destabilizes asset prices. My work is also related to the literature on fire sales (Shleifer and Vishny, 1992; Coval and Stafford, 2007; Shleifer and Vishny, 2011; Cella, Ellul, and Giannetti, 2013; Merrill, Nadauld, Stulz, and Sherlun, 2021) and contagion in financial markets (Kyle and Xiong, 2001; Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Boyson, Stahel, and Stulz, 2010; Aragon and Strahan, 2012).

Finally, this paper is related to the limits of arbitrage literature (Shleifer and Vishny, 1997; Vayanos and Gromb, 2010) and the slow-moving capital literature (Pedersen, Mitchell, and Pulvino, 2007; Duffie, 2010) as it studies a source of inelastic asset demand among institutional investors.

The paper proceeds as follows. Section 2 describes the data and presents suggestive evidence of institutional trading behavior. Section 3 presents the model that guides my empirical work. Section 4 presents evidence of the price impact of institutional investors' correlated demand shocks. Section 5 explores the asset pricing implications of the findings. Section 6 concludes.

2 Data and Motivating Facts

2.1 Data

I obtain firm-level data from the Center for Research in Security Prices (CRSP) and Compustat. I gather 13F institutional ownership and disaggregated fund-level ownership data from Thomson Reuters. The fund-level returns and cash holdings data come from the CRSP Survivor-Bias-Free Mutual Fund Database. The Russell 1000 and 2000 index weights data are from Compustat. I include ordinary common shares (CRSP share codes 10 or 11) traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership in the previous quarter. The sample period is from 1980 Q2 to 2020 Q2. I provide detailed data sources in Appendix A and variable descriptions in Appendix B.

2.2 Motivating Facts

Institutional investors' performance is generally defined relative to a market-wide benchmark index such as the S&P 500. Therefore, when the market performs well, institutional investors have a stronger incentive to perform better to catch up with the market's performance. This incentive can induce procyclical risk-taking behavior among institutional investors, making the direction of their stock trading covary with the direction of market movements.

For intuition, consider a portfolio manager of an equity-only fund worth $100 million with a mandate to beat a broad-market benchmark index, such as the Russell 1000. She has invested $95 million in stocks and saved $5 million as cash reserves to guard against the possibility of a sudden redemption. Suppose that the market has been performing well during the quarter, but her fund has underperformed the market. To preempt outflows from disappointed clients, she must find a way to improve her performance. This situation creates a strategic incentive for her to increase the riskiness of her fund. Consequently, she would allocate the cash reserves into equity (or even leverage her portfolio if allowed) since a higher equity exposure means a higher expected return with additional risk.

Suppose that a few months later, the stock market unexpectedly crashes. Because the manager took on additional risk by increasing her fund's equity exposure, her fund would be severely affected by the downturn. Disappointed investors would interpret her poor performance as partly due to a lack of skill and thus withdraw their investment. The fund manager does not have a high enough liquidity buffer (her fund is fully invested in equity) and therefore has to liquidate her positions aggressively to meet redemptions. In this example, the direction of her stock trading coincided with the direction of market movements in both market upturns and downturns.

Importantly, institutional investors act similarly as a group because they are typically in a similar situation. Panel (a) of Figure 1 shows that a higher fraction of institutional investors underperform the market when the market performs better. Consequently, as the market rises, more institutional investors are incentivized to increase the riskiness of their funds. Consistent with intuition, I find that institutional investors decrease their cash holdings in aggregate (Panel (b)) and tend to become net stock buyers (Panel (c)) when the market performs well.[9] The patterns are consistent with the intuition that asset managers increase the equity exposure of their portfolios partly with their cash reserves to catch up with the market's performance. The results suggest that the direction of institutional investors' stock trading tends to covary with the market's movements.

The magnitude of aggregate changes in cash holdings in Figure 1 is at most 0.5 percentage points in absolute terms. This amount would not be large enough to have aggregate price impacts. However, the figure misses the fact that some institutional investors can leverage their portfolios. Institutional investors who are leverage-constrained (e.g., mutual funds) would first use their cash holdings and then shift toward risky stocks to further increase the riskiness of their funds (Black, 1972; Frazzini and Pedersen, 2014). Panel (d) illustrates this

[9] I study the cash management of mutual funds because cash positions for 13F institutional investors are not observable.

point. The figure shows that more institutional investors shift toward high-beta stocks when the market performs well.

3 A Simple Model

I develop and estimate a simple model that embodies the facts documented in the previous section. My aim is to study the cross-sectional variation in stocks' exposure to institutional investors' correlating demand shocks. In other words, the model asks which stocks are most affected by the tendency among institutional investors to buy (sell) stocks when the market rises (falls). The setup is highly stylized but useful because it guides empirical work in a simple manner. In particular, the nature of demand shocks is exogenously specified, motivated by the suggestive evidence in the previous section. However, Appendix C shows that the key economic forces prevail in a more realistic model, building on the framework of Basak and Pavlova (2013). In this general equilibrium model, demand shocks arise endogenously due to institutional investors' incentives to beat a similar market index. Appendix D provides proofs.

3.1 Asset Returns

Consider an economy with n risky assets in fixed unit supply, indexed by $k = 1, ..., n$, and m institutional investors, indexed by $i = 1, ..., m$. Similar to Barberis et al. (2005), I model the return of asset k as

$$r_{k,t} = \underbrace{r^F_{k,t}}_{\text{Fundamental shock}} + \underbrace{\sum_i r^D_{i,k,t}}_{\text{Demand shocks}}, \tag{1}$$

where $r^F_{k,t}$ is asset k's fundamental shock, and $r^D_{i,k,t}$ is the effect of investor i's demand shock on asset k. Intuitively, the return of asset k can be decomposed into the fundamental shock and the sum of demand shocks across investors who trade asset k. Equation 1 implies that the return is affected by demand shocks only if a significant enough fraction of investors trade in the same direction. In contrast, if the shocks cancel each other out, their sum ($\sum_i r^D_{i,k,t}$) will be close to zero with a negligible price impact.

3.2 Fundamental Shocks

The fundamental shock, $r^F_{k,t}$, follows a factor structure, defined as

$$r^F_{k,t} = \phi_k \cdot f_t + \epsilon^F_{k,t}, \tag{2}$$

where ϕ_k is a fundamental factor loading, f_t is the market factor, and $\epsilon^F_{k,t}$ is the idiosyncratic shock. I consider a single-factor model for simplicity, yet the structure can be easily extended to a multifactor framework.

3.3 Demand Shocks

Each investor manages a fund and invests in risky assets. Letting Δ represent the difference operator (i.e., $\Delta x_t = x_t - x_{t-1}$), I model the effect of investor i's demand shock on asset k as

$$r^D_{i,k,t} = \frac{\Delta A_{i,t} \cdot \pi_{i,k,t-1}}{v_{k,t-1}}, \tag{3}$$

where $A_{i,t}$ is fund i's total investment in risky assets at time t; $\pi_{i,k,t-1}$ is a weight function that determines how fund i distributes its demand shocks across different assets; and the weights satisfy

$$\sum_{k \in K_{i,t-1}} \pi_{i,k,t-1} = 1, \tag{4}$$

with $K_{i,t-1}$ denoting the collection of risky assets in investor i's portfolio at time $t-1$. Finally, $v_{k,t-1}$ is asset k's market value at time $t-1$.

The change in investment in risky assets ($\Delta A_{i,t}$) in Equation 3 captures the dollar flow into or out of risky assets and is non-zero only when the fund makes trades (i.e., purchases additional risky assets or sells its current holdings). Intuitively, once investor i is hit with a dollar demand shock $\Delta A_{i,t}$, he buys or sells risky assets in a way that effectively splits his demand shock among the assets he owned prior to the demand shock, leading to a dollar flow of $\Delta A_{i,t} \cdot \pi_{i,k,t-1}$ into (if positive) or out of (if negative) asset k. The division by asset value $v_{k,t-1}$ in Equation 3 simply translates from this dollar flow to the demand shock effect on the asset return. Appendix E explores an alternative specification that translates from the dollar flow to the return effect using asset k's trading volume instead of its market equity. The empirical results are similar to those reported in the main text.

I now specify the nature of investor demand shocks ($\Delta A_{i,t}$) and how investors distribute the demand shocks across assets ($\pi_{i,k,t-1}$). First, investor demand shocks follow the factor structure

$$\frac{\Delta A_{i,t}}{A_{i,t-1}} = \theta_i \cdot f_t + \epsilon_{i,t}^D, \tag{5}$$

where θ_i is a demand factor loading, f_t is the market factor, and $\epsilon_{i,t}^D$ is the idiosyncratic demand shock. If the direction of investor i's asset trading coincides with the direction of market movements (which is the mechanism I propose for correlated demand shocks), then $\theta_i > 0$.

Second, the weight function that distributes investor i's demand shocks across assets is a function of two variables: the portfolio weight on asset k ($w_{i,k,t-1}$) and the asset ownership ratio in asset k ($s_{i,k,t-1}$). Specifically,

$$\pi_{i,k,t-1} = w_{i,k,t-1} \cdot \left(1 - \lambda_i \cdot s_{i,k,t-1}\right) + \psi_{i,t-1}, \tag{6}$$

where λ_i is a parameter to be estimated, and $\psi_{i,t-1}$ is a term that is solved to satisfy Equation 4.

To understand the intuition underlying Equation 6, note that in the special case in which investor i does not change his portfolio weights after a demand shock (i.e., $w_{i,k,t} = w_{i,k,t-1}$ as in Edmans et al. (2012)), the dollar flow for asset k is $w_{i,k,t} \cdot A_{i,t} - w_{i,k,t-1} \cdot A_{i,t-1} = w_{i,k,t-1} \cdot \Delta A_{i,t}$, which is equivalent to $\pi_{i,k,t-1} = w_{i,k,t-1}$ and thus implies $\lambda_i = 0$. (Note that, in this case, $\psi_{i,t-1} = 0$ to satisfy Equation 4.)

The specification in Equation 6 allows for a more general weight function that incorporates the possibility that institutional investors are cautious in trading an asset in which they have a large ownership stake (i.e., high $s_{i,k,t-1}$). A large asset ownership ratio implies that the investor's presence is large relative to the asset's total market value. Therefore, the size of his trades on this asset tends to be large compared to the asset's market value, potentially impacting prices (see Equation 3). With this possibility in mind, a large investor may not simply maintain his portfolio weights but rather tends to reduce the size of his trades, more so as his prior ownership is larger (i.e., $\lambda_i > 0$), trying to minimize his price impacts. Appendix E explores an alternative specification in which the concern about price impacts is a function of an asset's ownership scaled by trading volume instead of total shares outstanding. The empirical results are similar to those reported in the main text.

I now derive the implications of my demand shock specification for the return of asset k. Combining Equation 1 and Equation 3 results in

$$r_{k,t} = r^F_{k,t} + \frac{1}{v_{k,t-1}} \sum_i \Delta A_{i,t} \cdot \pi_{i,k,t-1}. \tag{7}$$

Equation 7 can be further combined with factor structures in Equation 2 and Equation 5 to yield

$$r_{k,t} = \left[\phi_k + \frac{1}{v_{k,t-1}} \sum_i \theta_i \cdot A_{i,t-1} \cdot \pi_{i,k,t-1}\right] f_t + \epsilon^*_{k,t}, \tag{8}$$

where $\epsilon^*_{k,t}$ is the sum of idiosyncratic shocks, given as

$$\epsilon^*_{k,t} = \epsilon^F_{k,t} + \frac{1}{v_{k,t-1}} \sum_i \epsilon^D_{i,t} \cdot A_{i,t-1} \cdot \pi_{i,k,t-1}.$$

Equation 8 demonstrates that the systematic risk of asset k is potentially a function of its fundamental market exposure and the sum of demand shocks across investors.

Finally, substituting the weight specification from Equation 6 into Equation 8 delivers the final specification for the asset k return:

$$r_{k,t} = \left[\phi_k + \frac{1}{v_{k,t-1}} \sum_i \theta_i \cdot A_{i,t-1} \cdot \Big(w_{i,k,t-1} \cdot \big(1 - \lambda_i \cdot s_{i,k,t-1}\big) + \psi_{i,t-1}\Big)\right] f_t + \epsilon^*_{k,t}, \tag{9}$$

which can be written as below in terms of expected returns:

$$\mathbb{E}\big[r_{k,t+1}\big] = \left[\phi_k + \frac{1}{v_{k,t}} \sum_i \theta_i \cdot A_{i,t} \cdot \Big(w_{i,k,t} \cdot \big(1 - \lambda_i \cdot s_{i,k,t}\big) + \psi_{i,t}\Big)\right] \cdot \mathbb{E}\big[f_{t+1}\big]. \tag{10}$$

Equation 10 shows that assets' expected returns are simply determined by the capital asset pricing model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966) but with endogenous betas. Further, an asset's beta can be decomposed into its fundamental market exposure (ϕ_k) and its endogenous market exposure arising from correlated demand shocks.

For the rest of the paper, I set $\phi_k = \phi$, $\theta_i = \theta$, and $\lambda_i = \lambda$ since my objective is to understand how much variation in risk premia the correlated demand shocks channel can capture in the absence of other heterogeneity effects.

3.4 Benchmark Case: Institutional Investors Do Not Internalize Price Impact of Their Trades

Edmans et al. (2012) make an implicit assumption about the weight function in Equation 6, which has an interesting implication for asset returns in my setting. In particular, they posit that a fund will trade assets in proportion to its current holdings, maintaining its portfolio weights. In other words, they model $\pi_{i,k,t-1} = w_{i,k,t-1}$, where $w_{i,k,t-1}$ is investor i's portfolio weight on asset k. With this assumption, Equation 8 collapses to

$$r_{k,t} = \left[\phi + \theta \cdot \sum_i s_{i,k,t-1}\right] f_t + \epsilon^*_{k,t}, \tag{11}$$

where $\sum_i s_{i,k,t-1}$ is the total institutional ownership ratio of asset k. In this special case, the systematic risk of asset k is potentially a function of its fundamental market exposure and the total institutional ownership ratio.

3.5 Estimation

Setting $\phi_k = \phi$, $\theta_i = \theta$, and $\lambda_i = \lambda$ yields the final equation to be estimated (Model I):

$$\mathbb{E}\big[r_{k,t+1}\big] = \Bigg[\underbrace{\phi \cdot \mathbb{E}\big[f_{t+1}\big]}_{\alpha} + \underbrace{\theta \cdot \mathbb{E}\big[f_{t+1}\big]}_{\beta} \cdot \frac{1}{v_{k,t}} \sum_i A_{i,t} \cdot \Big(w_{i,k,t} \cdot \big(1 - \lambda \cdot s_{i,k,t}\big) + \psi_{i,t}\Big)\Bigg]. \tag{12}$$

The parameter of interest is λ. Therefore, my goal is not to estimate ϕ, θ, and $\mathbb{E}\big[f_{t+1}\big]$ separately. Instead, I set $\phi \cdot \mathbb{E}\big[f_{t+1}\big] = \alpha$ and $\theta \cdot \mathbb{E}\big[f_{t+1}\big] = \beta$ and then estimate α, β, and λ, which can be done via nonlinear least squares.

For comparison, I also estimate the benchmark model (Edmans et al., 2012). Specifically, in terms of expected returns, Equation 11 can be written as below (Model II):

$$\mathbb{E}\big[r_{k,t+1}\big] = \Bigg[\underbrace{\phi \cdot \mathbb{E}\big[f_{t+1}\big]}_{\alpha} + \underbrace{\theta \cdot \mathbb{E}\big[f_{t+1}\big]}_{\beta} \cdot \sum_i s_{i,k,t}\Bigg]. \tag{13}$$

By setting $\phi \cdot \mathbb{E}\big[f_{t+1}\big] = \alpha$ and $\theta \cdot \mathbb{E}\big[f_{t+1}\big] = \beta$ as above, Equation 13 can be estimated with ordinary least squares.

I estimate Equations 12 and 13 for my sample of institution investors from 1980 Q2 to 2020 Q2. Following the recommendation in Hou, Xue, and Zhang (2020), I use value weights (one-quarter-lagged market capitalization) in estimating the models. Appendix E shows that the results are almost identical when using equal weights in estimating the models. The estimation procedure is detailed in Appendix E.

Table 1 shows that the estimated α is positive in both models, suggesting positive loadings on fundamental shocks. The estimated β is also positive in both models, implying that θ is positive (see Equation 5). The results suggest that, on average, institutional investors' demand shocks positively correlate with fundamental shocks. Importantly, the estimated λ is positive, suggesting that institutional investors are cautious when trading assets with high ownership (see Equation 6). The likelihood ratio shows that Model I provides a more powerful description of variation in asset returns than Model II (benchmark). Overall, the estimation results suggest that institutional investors' concerns about the price impacts of their trades affect their trading decisions.

Given the signs of the estimated parameters, Equation 12 provides a measure for a stock's endogenous market exposure due to correlated demand shocks (model-implied exposure):

$$\frac{1}{v_{k,t}} \cdot \underbrace{\sum_i \cdot A_{i,t} \cdot \left(w_{i,k,t} \cdot \left(1 - \lambda \cdot s_{i,k,t}\right) + \psi_{i,t} \right)}_{\equiv \sum_{k,t}} . \tag{14}$$

The model-implied exposure provides a mapping of asset characteristics to endogenous betas, which is the sum of the expected amount of correlated trades across institutional investors ($\sum_{k,t}$) scaled by an asset's market value ($v_{k,t}$). Intuitively, the price of a stock is potentially affected by correlated demand shocks when the expected correlated trading pressure is large relative to its market value.

3.6 A Simple Proxy for Endogenous Risk Exposure

The model-implied exposure further motivates a simple empirical proxy for $\sum_{k,t}$, the number of institutional owners (NIO). This simple measure does a good job of predicting the sum of correlated trades across institutional investors. In particular, the rank correlation between $\sum_{k,t}$ and NIO is very high (96%). Intuitively, a large number of owners implies a large and dispersed ownership structure.[10] Because the ownership structure is dispersed, each owner is small compared to the asset's total market value or trading volume. Therefore, each owner is not particularly concerned about the price impact of their trades. However, when demand shocks are correlated across institutional owners, the price impact can be large in aggregate because they trade in the same direction without worrying about their price impact from each owner's perspective.

While economically appealing, what makes the proxy particularly useful is its empirical tractability. To construct NIO, one simply needs to count the number of institutional stockholders, which makes it nearly free from measurement error. In contrast, ownership data (e.g., the number of shares owned reported by institutional investors) typically have a non-negligible number of erroneous or extreme observations. Such observations make the model-implied exposure relatively noisier since it is the sum of ownership-related variables from many investors. Nevertheless, the model-implied exposure is still useful in capturing stocks' exposure to correlated demand shocks. NIO is a simple yet empirically powerful proxy that embodies the economic forces of the estimated model.

In the main tests, I present two sets of results using the model-implied exposure and NIO. In regression analyses, the main independent variable is the natural log of $\sum_{k,t}$ or NIO, and I control for firm size (among other variables). Taking the log is a reasonable way to account for the highly stylized nature of my model and minimize the effects of erroneous or extreme observations. Taking the log of the model-implied exposure with the firm size control results in the following regression specification:

$$\begin{aligned} y_{k,t+1} &= \alpha + \beta \cdot ln(\Sigma_{k,t}/v_{k,t}) + \gamma \cdot ln(v_{k,t}) + \ldots + \epsilon_{k,t+1} \\ &= \alpha + \beta \cdot ln(\Sigma_{k,t}) + (\beta - \gamma) \cdot ln(v_{k,t}) + \ldots + \epsilon_{k,t+1}, \end{aligned} \tag{15}$$

where $y_{k,t+1}$ is either asset returns or market betas. The specification shows that one can

[10]NIO is positively correlated with total 13F ownership (80%) and is negatively correlated with institutional ownership concentration (−81%) in the data.

use the log of $\sum_{k,t}$ and control for the log of market equity in regressions. Since $\sum_{k,t}$ and NIO are highly correlated, one can consider a linear mapping between the log of the two variables. Indeed, the cross-sectional correlation between $ln(\sum_{k,t})$ and $ln(NIO_{k,t})$ is 89%. Consequently, I can replace $ln(\sum_{k,t})$ with $ln(NIO_{k,t})$ in Equation 15 as an approximation of the original specification.

For the empirical tests, I first present the results with log specifications and use the percentile ranks of these variables for the rest of the analyses. I do so because in the latter analyses, I investigate heterogeneity across institutional investors (e.g., the number of winning vs. losing funds) and compare the economic significance across the groups. The percentile rank is helpful since one can directly compare the magnitude of coefficients, especially when multiple variables are included in a single regression.

In portfolio analyses, the model-implied exposure (estimated with an expanding window) can be used as a single sorting variable. However, the case of NIO is not straightforward. For example, dividing NIO by market equity is troublesome as the units of the two variables are not comparable. To account for the different scales between NIO and market equity, I follow the approach in Nagel (2005) and construct a variable, Residual NIO, which is the estimated residuals from cross-sectional regressions of the log of NIO on the log of market equity:

$$ln(NIO_{k,t}) = a + b \cdot ln(v_{k,t}) + \epsilon_{k,t}. \tag{16}$$

The estimated coefficients $\hat{a}$ and $\hat{b}$ in each period adjust for different scales between the two variables and provide a way to use NIO adjusted for firm size as a single sorting variable. The rank correlation between the model-implied exposure and Residual NIO is 59%, indicating that the cross-sectional regressions did a reasonably good job in approximating the model-implied exposure with NIO adjusted for firm size. Residual NIO is a simple yet empirically powerful proxy that incorporates the economics of the model-implied exposure.

4 Price Impact of Correlated Demand Shocks

The previous section provides useful predictions that guide my empirical work. The parameter estimates in the model show that institutional investors' demand shocks covary with market movements. The following subsection investigates whether these correlated demand shocks lead to higher market betas in the cross-section. Guided by the model, I then use the model-implied exposure or the number of 13F institutional owners (NIO) as a proxy for a stock's exposure to institutional investors' correlated demand shocks.

4.1 Amplification of Systematic Risk

I run Fama and MacBeth (1973) regressions to study the relationship between stocks' exposure to correlated demand shocks and market betas in the cross-section. The market betas are computed by regressing daily stock returns in excess of the risk-free rates on contemporaneous and lagged value-weighted market returns in excess of the risk-free rates.[11] The dependent variable is the sum of the two estimated coefficients. Controls include stock characteristics such as firm size, the book-to-market ratio, past returns, and lagged market betas.

The first two columns of Table 2 follow the specifications in Equation 15. The results show that the model-implied exposure and NIO both have strong explanatory power for the cross-section of market betas. To easily compare the economic significance across variables, I use the percentile rank of the model-implied exposure or NIO as the main independent variable for the remaining analyses. The economic magnitude is sizable. Table 2 shows that a percentile rank increase of 50 for the model-implied exposure or NIO is associated with an increase in a market beta of 0.4. Taking annualized volatility of the stock market as 15%, this corresponds to a 6-percentage-point increase in systematic volatility.[12]

[11] I include lagged market returns to adjust for nonsynchronous trading (Dimson, 1979). The inferences remain unchanged when I do not make this adjustment or when I include other leads and lags of the market.

[12] Appendix Table A.III presents mixed findings for idiosyncratic volatility. NIO positively predicts idiosyncratic volatility, but the model-implied exposure does not.

The documented relationship is consistent with the notion that when the market performs well, institutional investors have a stronger incentive to perform better and thus buy more stocks to increase the riskiness of their funds. Their correlated trading covaries with market movements, inducing stocks to excessively comove with the market.

One could argue that the documented patterns arise because of flows from underlying investors. If funds receive correlated flows when the market performs well, institutional investors will generate the same trading patterns for a different reason, i.e., flows from their clients. In principle, the model I estimate does not take a stand on which channel drives correlated demand, and both channels can play a role. Empirically, I conduct several tests to distinguish between the two and find that flow-induced trading is not the leading cause of the observed trading behavior for institutional investors.

First, using disaggregated fund-level data, I show that the relation primarily originates from active rather than passive funds (Table 2). If institutional investors' discretionary trading drives the results, one would expect to see stronger effects among the active funds because the passive funds are buy-and-hold investors. The passive funds would exhibit the correlated trading behavior only if they received correlated flows from their client-investors, and the last column shows that correlated flows do play a role, though the magnitude is relatively small.

Second, I split active mutual funds into two groups: those that receive flows in the same direction as the market (high-flow funds) and the rest (low-flow funds). I then rerun the quarterly Fama and MacBeth (1973) regressions. The results, presented in Table 3, show that market betas are stronger for the latter group of funds (i.e., either without flows or with flows that move in the opposite direction of the market).[13] The stronger results for low-flow funds are shown in Columns (1), (2), and (3). These results may be puzzling at face value because one would not expect low-flow funds to exert strong buying pressure when the market performs well. However, during market upturns, there are no systematic outflows,

[13]The results are stronger for market upturns. Conversely, when the market performs poorly, the magnitudes are similar between the two groups (not reported).

while funds share a systematic incentive to increase equity exposure.

Third, earlier evidence in Section 2 shows that mutual funds decrease their cash holdings and buy more stocks when the market rises, which is consistent with their incentive to increase equity exposure. Finally, further supporting the risk-taking channel, I show that the results are stronger for funds that have underperformed the market (Columns (4), (5), and (6) in Table 3).[14] Based on this evidence, in Appendix C, I develop a general equilibrium model populated by institutional investors and show that correlated demand shocks can arise from the procyclical risk-taking channel.

The estimated model in Section 3 shows that the model-implied exposure and NIO should better capture a stock's exposure to correlated demand shocks than total institutional ownership. To test this prediction, I compare the explanatory power of other potential proxies for demand shocks, including total 13F institutional ownership and the Herfindahl-Hirschman index (HHI) of 13F institutional ownership. I find that the model-implied exposure and NIO are the strongest variables, as indicated by the estimated model.

Table 4 presents the results. Columns (3) and (4) show that 13F ownership and the HHI also predict the cross-section of market betas in the expected direction, yet the economic magnitudes are much smaller. In Column (5), I include all three variables and find that the model-implied exposure has strong explanatory power when controlling for the other measures. Column (6) shows that NIO dominates the other measures.

4.2 Identification Using a Fuzzy Regression Discontinuity Design

Another potential concern is the endogeneity of the proxies for stocks' exposure to correlated demand shocks. For instance, since the measures reflect investors' trading decisions, they may be simply picking up fundamentals. To address this issue, I use the Russell 1000 and 2000 annual reconstitution events as quasi-natural experiments. These events cause a sharp change in the number of active institutional owners, especially among stocks close to

[14]Appendix Table A.IV shows that the effects are stronger among high-beta stocks, which is consistent with the risk-taking motive for institutional investors.

the Russell 1000 and 2000 cutoffs. I confirm that the relation between market betas and the number of active funds holds in a fuzzy regression discontinuity setting, supporting a causal interpretation of the findings.

The annual reconstitution events between the Russell 1000 and 2000 occur in June. Until 2006, the first 1,000 largest stocks comprise the Russell 1000, and the following 2,000 largest stocks comprise the Russell 2000 based on end-of-May market capitalization rankings.[15] However, Russell does not publicly disclose how it constructs the ranking variable for the annual reconstitution. Therefore, one needs to construct a proxy that closely resembles Russell's methodology, a task that turns out to be quite difficult. Moreover, prior studies suggest that the implementation of this regression discontinuity setting should be conducted carefully (Appel et al., 2020). For the implementation, I closely follow a methodology proposed by Ben-David et al. (2019). The authors find a substantial improvement for the approximation of the market capitalization rankings that Russell uses for index assignment, combining information from CRSP and Compustat.[16]

I argue that there is likely to be a discontinuity in the number of active funds around the Russell 1000 and 2000 cutoffs. Specifically, I expect to observe that stocks whose market capitalization rankings are just above the cutoff (joining the Russell 1000) are likely to have more active owners than stocks just below the cutoff (joining the Russell 2000). The reasons are as follows. First, active funds' investment mandates typically constrain managers from picking stocks that do not comprise large-cap indexes such as the S&P 500 and the Russell 1000. Second, active funds' performance also tends to be benchmarked to the large-cap benchmark indexes, and sometimes funds are required to hold a large proportion of stocks that comprise their benchmark indexes. Therefore, the stocks that comprise the Russell 1000 index are likely to have more active owners following the reconstitution events, and the difference is likely greater around the cutoff points.

[15] After 2006, Russell introduced a banding rule, which significantly reduces variation around the cutoffs between the two indexes.

[16] See Ben-David et al. (2019) and Appel et al. (2020) for a comprehensive discussion.

To test the conjecture, I begin by running first-stage regressions. Specifically, the independent variable of interest is a treatment variable, an indicator that equals one if a stock is expected to be included in the Russell 1000 index based on its market capitalization ranking in May. I investigate four different narrow bandwidths — ±50, ±75, ±100, and ±125 — and control for polynomials of the market capitalization ranking variable to the third-order as well as their interaction terms with the treatment variable.

The results in Panel A of Table 5 indicate the existence of a discontinuity in the number of active funds around the Russell 1000 and 2000 cutoff points. The magnitude of the discontinuity is around 60, and it is statistically significant at a 1% level regardless of the bandwidth selection. Panel (a) of Figure 2 visually confirms the discontinuity, and Panel (a) of Appendix Figure A.II shows that there is no discontinuity before the reconstitution dates.[17]

After confirming the existence of a discontinuity, I then use the treatment variable, which predicts whether a stock is expected to be included in the Russell 1000 index, as an instrument for the number of active funds following the reconstitution dates. The dependent variable of interest is the market beta estimated using daily stock returns within each quarter as in Table 2. Again, I investigate four different narrow bandwidths — ±50, ±75, ±100, and ±125 — and control for polynomials of the market capitalization ranking variable to the third-order as well as their interaction terms with the treatment variable. I control for stock characteristics and the total active and passive fund ownership. To ensure that I capture any changes in ownership structures around the reconstitution events, I further control for changes in active and passive fund ownership.[18]

Panel B of Table 5 reports the second-stage regression results. I find that the relationship between the market betas and the number of active funds holds in the fuzzy regression discontinuity setting. A one-standard-deviation increase in the number of active funds leads

[17]Panel (b) of Figure 2 shows that there is a discontinuity in the number of passive funds. Unlike the number of active funds, stocks whose market capitalization rankings are just above the cutoff (joining the Russell 1000) have fewer passive owners than stocks just below the cutoff (joining the Russell 2000). Panel (b) of Appendix Figure A.II shows that there is no discontinuity before the reconstitution dates.

[18]The use of different control variables does not change the main results.

to a higher market beta of approximately 0.7, which is greater than the estimate from Table 2. The findings suggest that the relationship between the market betas and the number of active funds is likely to be causal.[19]

One might conjecture that I find an increase in stocks' market exposure due to an "index effect." In particular, stocks that comprise the Russell 1000 may exhibit excessive comovement with the Russell 1000 (i.e., the market portfolio) because flows in and out of the Russell 1000 funds affect all stocks in the index. In a similar context, Barberis et al. (2005) find that stocks added to the S&P 500 index exhibit extra comovement with the S&P 500.[20] However, the results of previous studies that use the Russell 1000 and 2000 to examine demand from indexing suggest that my findings are not likely to originate from the index effect. Chang et al. (2015) show that index demand is very small for stocks just above the cutoff (joining the Russell 1000) but is large for those just below the cutoff (joining the Russell 2000). The reason for this disparity is that the index weights of the former stocks are minuscule. Empirically, I find no effects from passive funds. Therefore, I conclude that the active funds are likely driving the increased market exposure.

5 Asset Pricing Implications

The results in the previous section suggest that institutional investors' correlated demand shocks endogenously increase stocks' market risk. In this section, I examine whether the amplified market risk is priced in the cross-section.

[19]In principle, it is possible that a stock's discount rate shocks comove more with index shocks after the stock is included in the index. If this were the case, one would not be able to tell whether the relationship exists due to correlated demand shocks or the institutional preference for high-beta stocks (Black, 1972).

[20]Chen et al. (2016) document that the evidence of comovement disappears when using a more refined analysis.

5.1 Return Predictability

I run Fama and MacBeth (1973) regressions to test whether the model-implied exposure and NIO predict stock returns in the cross-section. The dependent variable is quarterly stock returns. Controls include stock characteristics that are known to predict stock returns in the asset pricing literature. For the return predictability test, I estimate Equation 12 in Section 3 on an expanding window of four quarters and form portfolios based on the resulting model-implied exposure.

The results are presented in Table 6. The first two columns follow the specifications in Equation 15. The results show that the model-implied exposure and NIO both have strong explanatory power for the cross-section of stock returns. The economic magnitude is sizable. A percentile rank increase of 50 for the model-implied exposure (NIO) is associated with an approximately 3-percentage-point (4-percentage-point) increase in quarterly stock returns. Consistent with the results in Table 2 that active funds are primarily responsible for stocks' increased market risk, I find that the return predictability is driven by active, not passive, funds.

The return predictability of NIO differs from the results in Chen et al. (2002), who show that changes in the number of mutual funds (i.e., change in breadth) predict returns. They argue that a reduction in breadth predicts abnormally low returns because this measure captures disagreement and binding short-sale constraints. In particular, a reduction in the number of mutual funds means that only optimists are holding stocks as many pessimists have already exited their positions, finding it difficult to sell short. Unlike Chen et al., I show that, controlling for firm size, the level of NIO (not the change) predicts returns because it captures the exposure of stocks to institutional investors' correlated trading pressures, which increase stocks' market risk. Importantly, the results in Table 6 show that the return predictability of NIO holds after controlling for the Chen et al. measure (change in breadth). Their measure also predicts returns, but its predictive power decays in the post-2000 period.

5.2 Portfolio Analysis

In this subsection, I conduct portfolio-based return predictability tests. I use the model-implied measure based on the rolling estimation of Equation 12 in Section 3 to form portfolios. For NIO to be used as a single sorting variable, I construct a variable, Residual NIO, which is the estimated residuals from cross-sectional regressions of NIO on firm size following Nagel (2005). Specifically, I regress the natural logarithm of 1 + NIO on the natural logarithm of market capitalization each month and form 10 portfolios based on the estimated residuals (Residual NIO) in the next month. The residuals are orthogonal to the size effect by construction. The 10 portfolios based on the model-implied exposure or Residual NIO are rebalanced monthly, and the portfolio returns are value-weighted.

Panel A of Table 7 reports the average returns and the market betas of the portfolios sorted by the model-implied exposure. The portfolio returns increase monotonically from the bottom decile portfolio (52 basis points per month) to the top decile portfolio (109 basis points per month), generating a return differential of 6.84% per year. Importantly, the return spread is fully explained by the portfolios' market betas. Specifically, the market betas increase from the bottom decile portfolio (0.73) to the top decile portfolio (1.12). The CAPM alpha of the long-short portfolio is neither economically nor statistically significant.

Panel B of Table 7 reports the average returns and the market betas of the Residual NIO-sorted portfolios. The results are stronger, and the main conclusion remains the same. The portfolio returns increase monotonically from the bottom decile portfolio (89 basis points per month) to the top decile portfolio (160 basis points per month), generating a return differential of 8.52% per year. The market betas increase monotonically from the bottom decile portfolio (0.93) to the top decile portfolio (1.44). The CAPM alphas of all portfolios are economically not different from zero, and none of them are statistically significant.[21]

In Appendix Table A.V, I replicate the results in Table 7 using total 13F institutional ownership and the Herfindahl-Hirschman index (HHI) of 13F institutional ownership. The

[21]The 4th decile portfolio is the exception, yet the economic magnitude of the CAPM alpha is not sizable.

results show similar but weaker patterns.

The documented patterns support the notion that institutional investors' correlated demand shocks endogenously increase stocks' market risk. The patterns in portfolio returns suggest that the amplified market risk is priced in the cross-section.

5.3 The Covariance Channel

The previous subsection shows that stocks' endogenous market exposure commands an 8.52% annual return premium in decile portfolios. Importantly, the differences in market betas across the portfolios quantitatively explain the return spreads. In this subsection, I further demonstrate that the return predictability of NIO originates from a covariance channel.

Kelly et al. (2019) provide a framework to test whether return predictability arises from covariance or implies anomalies. Specifically, they model the return of assets as

$$r_{k,t+1} = \underbrace{z_{k,t}^{'} \cdot \Gamma_\alpha}_{\alpha_{k,t}} + \underbrace{z_{k,t}^{'} \cdot \Gamma_\beta}_{\beta_{k,t}} \cdot f_{t+1} + \epsilon_{k,t+1}, \tag{17}$$

where $z_{k,t}$ is a $L \times 1$ vector of asset characteristics (L characteristics including constant); Γ_α and Γ_β are $L \times 1$ vectors of coefficients; and f_{t+1} is the risk factor. The model can be easily extended to a multifactor framework with unobservable factors. In Equation 17, both alphas and betas are potentially a function of asset characteristics (Rosenberg, 1974). In this framework, if an asset characteristic predicts returns because it proxies for a factor loading, then its effect on returns will show up through Γ_β (not Γ_α). With observable factors (i.e., the market factor), Equation 17 can be estimated using cross-sectional regressions. In my setting, I include the market factor as a single risk factor. The testing assets are the decile portfolios formed by the model-implied exposure or Residual NIO, and $z_{k,t}$ is a 2×1 vector with a constant and the model-implied exposure or Residual NIO (at the portfolio level, e.g., value-weighted Residual NIO).

Panel A of Table 8 presents the estimated coefficients of the model-implied exposure for alpha (the second element of Γ_α) and beta (the second element of Γ_β). The estimated coefficient for alpha is economically and statistically insignificant. In contrast, the estimated coefficient for beta does a good job of explaining the return spreads across the portfolios. The bootstrap test result shows that one cannot reject the null hypothesis $H_0 : \Gamma_\alpha = 0$. Specifically, the bootstrapped p-value is over 60%. In contrast, the p-value for the null hypothesis $H_0 : \Gamma_\beta = 0$ is slightly over 5%.

Panel B of Table 8 presents the estimated coefficients of Residual NIO for alpha and beta. The results are stronger. Specifically, the estimated coefficient for alpha is extremely small. In contrast, the estimated coefficient for beta does all the work in explaining the return spreads across the portfolios, strongly supporting the covariance channel. The bootstrapped p-value for the null hypothesis $H_0 : \Gamma_\alpha = 0$ is over 50%. In contrast, the p-value for the null hypothesis $H_0 : \Gamma_\beta = 0$ is below 1%.

The covariance channel manifests itself in bad times. Figure 3 presents anecdotal evidence from the global financial crisis of 2008. Specifically, the figure shows the performance and institutional ownership of the top and bottom portfolios based on the model-implied exposure or Residual NIO during the global financial crisis. First, the price declines of the top decile portfolios are substantially sharper than those of the bottom decile portfolios during the global financial crisis (Panels (a) and (b)). Moreover, the price declines coincide with institutional selling pressures (Panels (c) and (d)), especially for the portfolios formed by Residual NIO. Specifically, the median total institutional ownership of the stocks in the top Residual NIO decile portfolio decreased substantially (by 15 percentage points) during the global financial crisis of 2008.[22] In contrast, the median total institutional ownership of the stocks in the bottom Residual NIO decile portfolio remains relatively constant throughout the crisis period. The ownership results for the model-implied exposure are relatively weak. Specifically, the median ownership for the top decile portfolio decreased by only 6 percentage

[22]The median institutional ownership generates more reliable inferences than the average institutional ownership due to extreme observations in the 13F data.

points. This is because Residual NIO better captures the cross-sectional variation in risk exposure, particularly for the long leg (the riskiest stocks).

The anecdotal evidence in Figure 3 is generalizable. Panels C and D of Table 8 report the returns of the portfolios based on the model-implied exposure and Residual NIO, respectively, in months of stock market crashes, defined as months in which market returns are ranked in the bottom 10% of all months in the sample period. The results show that the average portfolio returns become more negative, moving from the bottom to the top decile portfolios. Importantly, the differential price crashes arise through the differences in market betas across the portfolios. The results are again stronger for the portfolios formed by Residual NIO.

6 Conclusion

This paper proposes a mechanism through which institutional investors' correlated demand shocks, caused by their incentive to beat a similar market index (e.g., the S&P 500), provide a source of risk exposure in the cross-section of stock returns. I show that this incentive induces procyclical risk-taking behavior among institutional investors, generating demand shocks that covary with the direction of market movements. These correlated demand shocks cause stocks to excessively comove with the market, amplifying their market risk. This endogenous risk translates into stock price crashes during market downturns and a return premium of 8.52% per year.

My findings suggest that institutional investors may influence firms' investment decisions through the cost of capital channel since many U.S. firms use the CAPM to measure their cost of equity (Graham and Harvey, 2001). Investigating whether this mechanism is in play will be an interesting avenue for future research.

Another important and interesting future direction would be to investigate the international finance implications of my findings since many institutional investors hold internationally well-diversified portfolios. One possibility is that institutional investors' demand shocks in a local market are transmitted to foreign markets through their portfolio management.

There is literature that interprets higher stock return R-squareds as indicative of a less efficient stock market (Morck, Yeung, and Yu, 2000). Bartram, Brown, and Stulz (2019) document a secular decline in idiosyncratic risk in the 2000s while the stock return R-squared increased during the same period. Perhaps institutional investors' correlated demand shocks contributed to this trend, causing stocks to excessively comove with the market for no fundamental reasons.

One might wonder whether the growth of passive investment implies that the effects I document have become less important. Indeed, the rise of passive investing means a decrease in the share of active players who produce noise in the stock market. However, the rise of passive investing also implies a decrease in the share of competitive players who have elastic demand. Interestingly, Haddad, Huebner, and Loualiche (2021) show that the stock market is becoming more inelastic over time due to the popularity of passive investing. Consequently, the same magnitude of demand shocks may generate a larger price impact as passive investors become increasingly more important players in financial markets.

References

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Appel, Ian, Todd A Gormley, and Donald B Keim, 2020, Identification using russell 1000/2000 index assignments: A discussion of methodologies, *Critical Finance Review,* forthcoming.

Aragon, George O, and Philip E Strahan, 2012, Hedge funds as liquidity providers: Evidence from the lehman bankruptcy, *Journal of Financial Economics* 103, 570–587.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–317.

Bartram, Söhnke M, Gregory W Brown, and René M Stulz, 2019, Why is there a secular decline in idiosyncratic risk in the 2000s?, Working paper.

Basak, Suleyman, and Anna Pavlova, 2013, Asset prices and institutional investors, *American Economic Review* 103, 1728–58.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2019, An improved method to predict assignment of stocks into russell indexes, Technical report, National Bureau of Economic Research.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 45, 444–455.

Boyer, Brian H, 2011, Style-related comovement: Fundamentals or labels?, *Journal of Finance* 66, 307–332.

Boyson, Nicole M, Christof W Stahel, and Rene M Stulz, 2010, Hedge fund contagion and liquidity shocks, *Journal of Finance* 65, 1789–1816.

Brennan, Michael, 1993, Agency and asset pricing, University of california at los angeles, anderson graduate school of management, Anderson Graduate School of Management, UCLA.

Brunnermeier, Markus K, and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Buffa, Andrea M, and Idan Hodor, 2022, Institutional investors, heterogeneous benchmarks and the comovement of asset prices, *Journal of Financial Economics* forthcoming.

Buffa, Andrea M, Dimitri Vayanos, and Paul Woolley, 2022, Asset management contracts and equilibrium prices, *Journal of Political Economy* forthcoming.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Cella, Cristina, Andrew Ellul, and Mariassunta Giannetti, 2013, Investors' horizons and the amplification of market shocks, *Review of Financial Studies* 26, 1607–1648.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2015, Regression discontinuity and the price effects of stock market indexing, *Review of Financial Studies* 28, 212–246.

Chen, Honghui, Vijay Singal, and Robert F Whitelaw, 2016, Comovement revisited, *Journal of Financial Economics* 121, 624–644.

Chen, Joseph, Harrison Hong, and Jeremy C Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171–205.

Cho, Thummim, 2020, Turning alphas into betas: Arbitrage and endogenous risk, *Journal of Financial Economics* 137, 550–570.

Choe, Hyuk, Bong-Chan Kho, and Rene M Stulz, 1999, Do foreign investors destabilize stock markets? the korean experience in 1997, *Journal of Financial Economics* 54, 227–264.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Cuoco, Domenico, and Ron Kaniel, 2011, Equilibrium prices in the presence of delegated portfolio management, *Journal of Financial Economics* 101, 264–296.

Dasgupta, Amil, Andrea Prat, and Michela Verardo, 2011, The price impact of institutional herding, *Review of Financial Studies* 24, 892–925.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

Dou, Winston Wei, Leonid Kogan, and Wei Wu, 2022, Common fund flows: Flow hedging and factor pricing, Technical report, National Bureau of Economic Research.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *Journal of Finance* 65, 1237–1267.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *Journal of Finance* 67, 933–971.

Evans, Richard B, Juan-Pedro Gómez, Linlin Ma, and Yuehua Tang, 2022, Peer versus pure benchmarks in the compensation of mutual fund managers, Working paper.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F, and Kenneth R French, 2018, Choosing factors, *Journal of Financial Economics* 128, 234–252.

Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

Giglio, Stefano, and Dacheng Xiu, 2021, Asset pricing with omitted factors, *Journal of Political Economy* 129, 1947–1990.

Graham, John R, and Campbell R Harvey, 2001, The theory and practice of corporate finance: Evidence from the field, *Journal of Financial Economics* 60, 187–243.

Greenwood, Robin, 2008, Excess comovement of stock returns: Evidence from cross-sectional variation in nikkei 225 weights, *Review of Financial Studies* 21, 1153–1186.

Greenwood, Robin, and David Thesmar, 2011, Stock price fragility, *Journal of Financial Economics* 102, 471–490.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361–407.

Haddad, Valentin, Paul Huebner, and Erik Loualiche, 2021, How competitive is the stock market? theory, evidence from portfolios, and implications for the rise of passive investing, in *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI-ESSEC*.

Han, Xiao, Nikolai L Roussanov, and Hongxun Ruan, 2022, Mutual fund risk shifting and risk anomalies, Working paper.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732–70.

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang, 2021, An augmented q-factor model with expected growth, *Review of Finance* 25, 1–41.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Hou, Kewei, Chen Xue, and Lu Zhang, 2020, Replicating anomalies, *Review of Financial Studies* 33, 2019–2133.

Kashyap, Anil K, Natalia Kovrijnykh, Jian Li, and Anna Pavlova, 2020, Is there too much benchmarking in asset management?, Technical report, National Bureau of Economic Research.

Kelly, Bryan T, Seth Pruitt, and Yinan Su, 2019, Characteristics are covariances: A unified model of risk and return, *Journal of Financial Economics* 134, 501–524.

Koch, Andrew, Stefan Ruenzi, and Laura Starks, 2016, Commonality in liquidity: a demand-side explanation, *Review of Financial Studies* 29, 1943–1974.

Koijen, Ralph SJ, and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.

Kyle, Albert S, and Wei Xiong, 2001, Contagion as a wealth effect, *The Journal of Finance* 56, 1401–1440.

Lakonishok, Josef, Andrei Shleifer, and Robert W Vishny, 1992, The impact of institutional trading on stock prices, *Journal of Financial Economics* 32, 23–43.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13–37.

Lou, Dong, 2012, A flow-based explanation for return predictability, *The Review of Financial Studies* 25, 3457–3489.

Menzly, Lior, Tano Santos, and Pietro Veronesi, 2004, Understanding predictability, *Journal of Political Economy* 112, 1–47.

Merrill, Craig B, Taylor D Nadauld, René M Stulz, and Shane M Sherlun, 2021, Were there fire sales in the rmbs market?, *Journal of Monetary Economics* 122, 17–37.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: why do emerging markets have synchronous stock price movements?, *Journal of Financial Economics* 58, 215–260.

Mossin, Jan, 1966, Equilibrium in a capital asset market, *Econometrica* 34, 768–783.

Mullally, Kevin, and Andrea Rossi, 2022, Moving the goalposts? Mutual fund benchmark changes and performance manipulation, Working paper.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Nofsinger, John R, and Richard W Sias, 1999, Herding and feedback trading by institutional and individual investors, *Journal of Finance* 54, 2263–2295.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Pavlova, Anna, and Taisiya Sikorskaya, 2022, Benchmarking intensity, Working paper.

Pedersen, Lasse Heje, Mark Mitchell, and Todd Pulvino, 2007, Slow moving capital, *American Economic Review* 97, 215–220.

Rosenberg, Barr, 1974, Extra-market components of covariance in security returns, *Journal of Financial and Quantitative Analysis* 9, 263–274.

Sharpe, William F, 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Shleifer, Andrei, and Robert Vishny, 2011, Fire sales in finance and macroeconomics, *Journal of Economic Perspectives* 25, 29–48.

Shleifer, Andrei, and Robert W Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, *Journal of Finance* 47, 1343–1366.

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Sias, Richard W, 2004, Institutional herding, *Review of Financial Studies* 17, 165–206.

Vayanos, D, and D Gromb, 2010, Limits of arbitrage, *Annual Review of Financial Economics* 2, 251–75.

Vayanos, Dimitri, 2004, Flight to quality, flight to liquidity, and the pricing of risk, Technical report, National Bureau of Economic Research.

Vayanos, Dimitri, and Paul Woolley, 2013, An institutional theory of momentum and reversal, *Review of Financial Studies* 26, 1087–1145.

Wermers, Russ, 1999, Mutual fund herding and the impact on stock prices, *Journal of Finance* 54, 581–622.

Figure 1. Direction of Institutional Investors' Stock Trading

The figure presents binned scatter plots showing the relationship between institutional investors' stock trading and market returns. Panel (a) shows the fraction of mutual funds that outperform the market. Panel (b) shows aggregate changes in active mutual funds' cash holdings (in percentage points). Panel (c) presents the fraction of institutional investors whose net dollar amount of trades for stocks is positive. In Panel (d), institutional investors are considered to shift toward high-beta stocks if their total dollar amount of trades for stocks with above-median market betas exceeds that for stocks with below-median market betas.

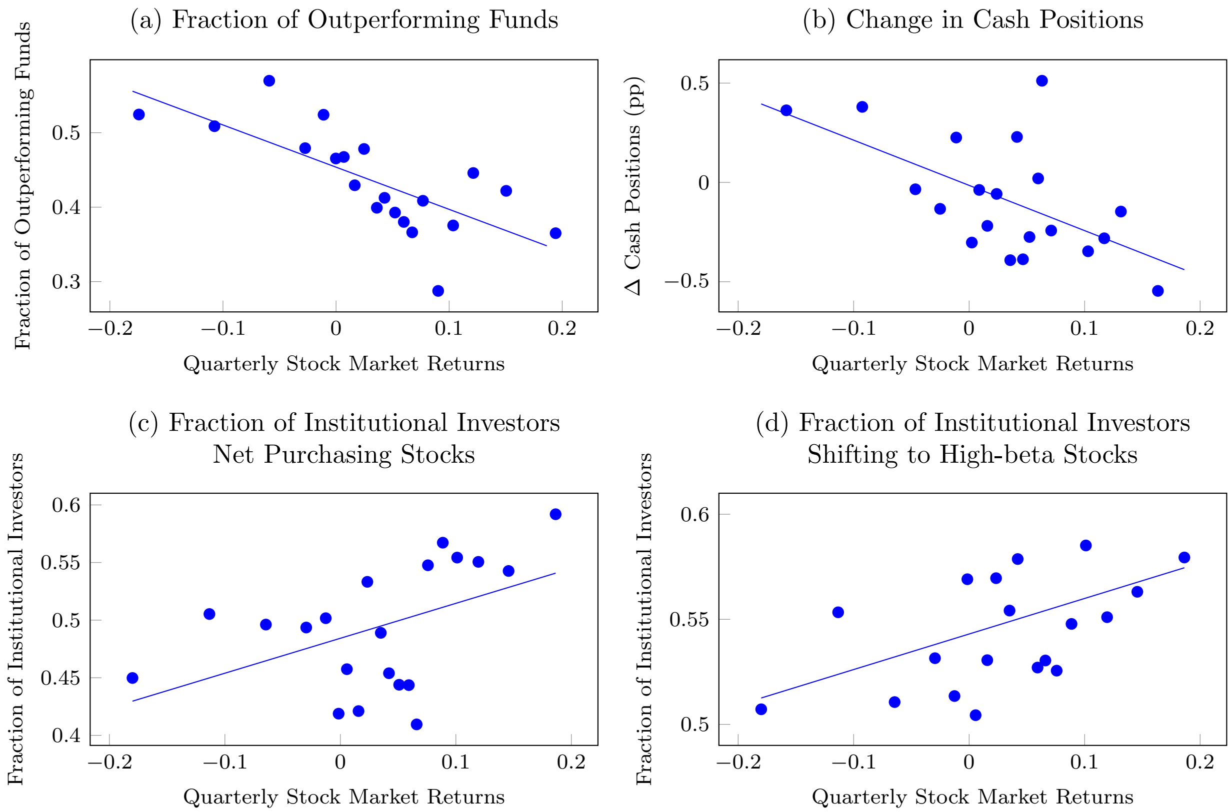


Figure 2. Number of Funds After Russell Reconstitution Events

The figure plots the number of active and passive owners in December (six months after the reconstitution events) against May (one month before the reconstitution events) market capitalization rankings. The sample period spans the Russell reconstitution events between 2000 and 2006. Panel (a) shows the number of active funds, and Panel (b) reports the number of passive funds. Rank is stocks' market capitalization rankings in May. Rank equals −200 (200) if a stock is ranked 800th (1,200th). Each bin represents the average of 10 ranks over the sample period. The solid lines are the fitted lines using linear polynomials with a triangular kernel centered on the cutoff rank 0.

(a) Number of Active Funds (b) Number of Passive Funds

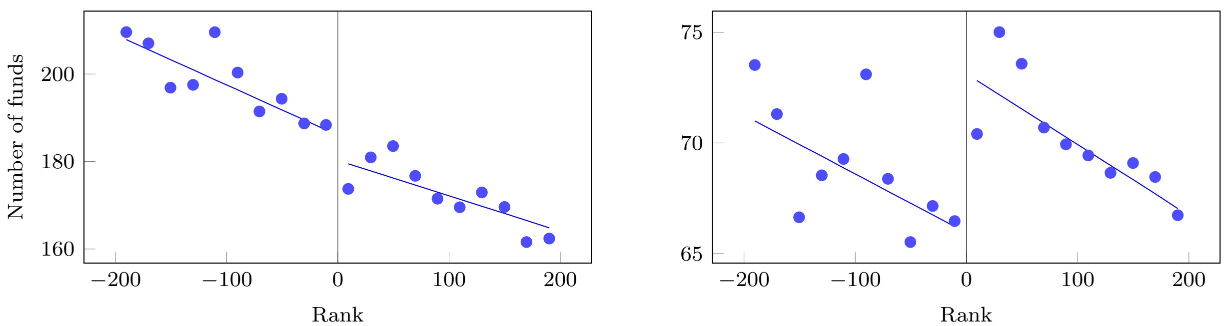


Figure 3. Portfolio Returns and Institutional Ownership During the Global Financial Crisis

The figure shows the cumulative returns and the median 13F institutional ownership of portfolios based on the model-implied exposure (Panels (a) and (b)) and Residual NIO (Panels (c) and (d)) during the global financial crisis in 2008. The portfolio formations are described in Table 7. Panels (a) and (c) present cumulative monthly returns of the top and the bottom decile portfolios, and Panels (b) and (d) report the median total 13F ownership of stocks in the top and the bottom decile portfolios.

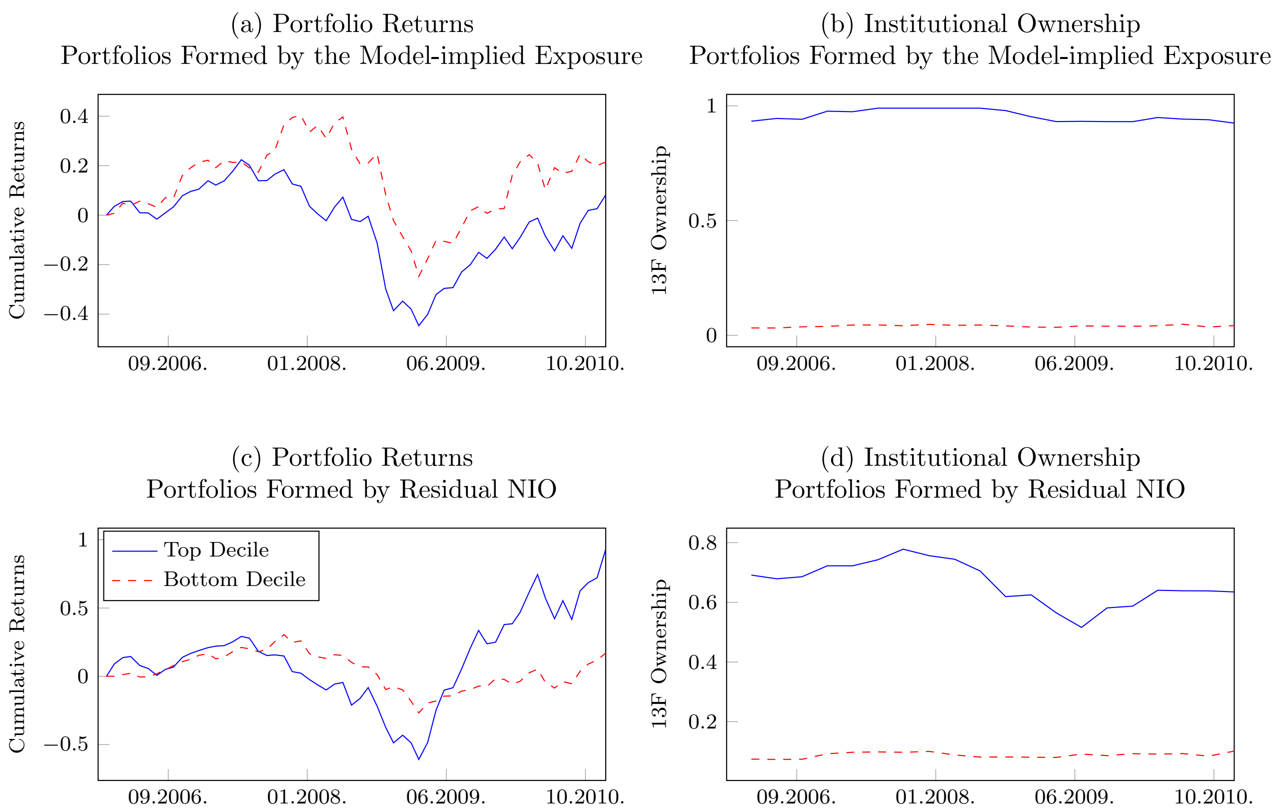


Table 1. Parameter Estimates and the Goodness of Fit

The table reports the parameter estimates from Equation 12 (Model I) and Equation 13 (Model II) with value weights and the likelihood ratio test. Model I incorporates institutional investors' concern about the price impact of their trades, which is summarized by a parameter (λ) added to Model II. Model II is the benchmark model following the assumptions in Edmans et al. (2012). I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership. Standard errors are reported in brackets. The estimation procedures are detailed in Appendix E.

	Model I	Model II
α	0.025	0.025
	[0.007]	[0.006]
β	0.151	0.021
	[0.075]	[0.009]
λ	7.736	–
	[2.986]	–
Likelihood ratio	9.95	–
p-value	0.002	–

Table 2. Amplification of Market Risk

The table reports quarterly Fama and MacBeth (1973) regressions of market betas on the model-implied exposure (from Equation 12 in Section 3) and the number of 13F institutional owners (NIO). I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership or negative book value from Compustat. The market betas are computed by regressing daily stock returns in excess of the risk-free rates on contemporaneous and lagged value-weighted market returns in excess of the risk-free rates. The dependent variable is the sum of the two estimated coefficients. The main independent variables are the log or the percentile rank of the model-implied exposure, the number of 13F institutional owners (NIO), the number of active funds, and the number of passive funds. Mktcap is the quarter-end market capitalization, and Price is the quarter-end stock price. Book-to-market is book equity divided by market equity; Assets growth is the change in assets scaled by lagged assets (Fama and French, 2015; Hou et al., 2015); and Profitability is revenue minus the cost of goods sold, scaled by total assets (Novy-Marx, 2013). Past-6-month return is the natural logarithm of cumulative past-6-month returns excluding the most recent month return. The Amihud ratio is computed within each quarter following Amihud (2002). t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Beta_{q+1}					
Sample period:	1980-2020	1980-2020	1980-2020	1997-2020	1980-2020	1997-2020
log(Model-implied exposure$_q$)	0.034***					
	(12.79)					
log(NIO$_q$)		0.163***				
		(18.02)				
Rank: Model-implied exposure$_q$			0.007***	0.007***		
			(18.46)	(13.16)		
Rank: NIO$_q$					0.008***	
					(19.19)	
Rank: NIO$_q$ (active)						0.006***
						(15.11)
Rank: NIO$_q$ (passive)						0.003***
						(4.98)
log(Mktcap$_q$)	−0.002	−0.060***	−0.049***	−0.063***	−0.060***	−0.084***
	(−0.32)	(−9.73)	(−8.57)	(−8.17)	(−9.61)	(−11.42)
1/Price$_q$	0.050***	0.027**	0.043***	0.073***	0.027**	0.056***
	(4.50)	(2.35)	(3.87)	(3.87)	(2.41)	(3.03)
log(Book-to-market$_q$)	−0.066***	−0.081***	−0.074***	−0.053***	−0.080***	−0.062***
	(−9.41)	(−11.04)	(−10.13)	(−5.31)	(−10.91)	(−6.46)
Assets growth$_{y-1}$	0.099***	0.110***	0.100***	0.070***	0.106***	0.084***
	(10.59)	(12.32)	(10.70)	(5.84)	(11.77)	(7.28)
Profitability$_{y-1}$	0.013	−0.011	−0.004	−0.050***	−0.012	−0.078***
	(1.03)	(−0.89)	(−0.37)	(−3.01)	(−0.99)	(−4.72)
Past-6-month return	−0.028	0.008	−0.026	−0.044	0.005	−0.015
	(−1.33)	(0.36)	(−1.23)	(−1.46)	(0.23)	(−0.52)
Amihud ratio$_q$	−0.048***	−0.044***	−0.053***	−0.088***	−0.050***	−0.085***
	(−7.18)	(−6.83)	(−7.23)	(−7.78)	(−7.03)	(−7.77)
Beta$_q$	0.242***	0.232***	0.237***	0.292***	0.230***	0.282***
	(21.12)	(20.73)	(20.93)	(19.26)	(20.77)	(19.23)
Observations	624,867	624,867	624,867	355,484	624,867	355,484
R-squared	0.170	0.176	0.173	0.211	0.177	0.218

Table 3. Alternative Explanations

The table reports quarterly Fama and MacBeth (1973) regressions of market betas on the number of active mutual funds. I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership or negative book value from Compustat. The market betas are computed by regressing daily stock returns in excess of the risk-free rates on contemporaneous and lagged value-weighted market returns in excess of the risk-free rates. The dependent variable is the sum of the two estimated coefficients. The main independent variables are the percentile rank of the number of high-flow, low-flow, winning, and losing funds. High-flow funds are those that receive flows moving in the same direction as the market. The rest are low-flow funds. Winning funds are those that have outperformed the market during the quarter. The rest are losing funds. Mktcap is the quarter-end market capitalization, Price is the quarter-end stock price, and Book-to-market is book equity divided by market equity. Assets growth is the change in assets scaled by lagged assets (Fama and French, 2015; Hou et al., 2015). Profitability is revenue minus the cost of goods sold, scaled by total assets (Novy-Marx, 2013). Past-6-month return is the natural logarithm of cumulative past-6-month returns excluding the most recent month return, and the Amihud ratio is computed within each quarter following Amihud (2002). t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Beta_{q+1}					
	(1)	(2)	(3)	(4)	(5)	(6)
Rank: NIO_{q+1} (high-flow)	0.002***		0.001***			
	(7.76)		(3.58)			
Rank: NIO_{q+1} (low-flow)		0.003***	0.003***			
		(11.11)	(9.60)			
Rank: NIO_{q+1} (winning)				0.001***		0.001***
				(4.44)		(3.73)
Rank: NIO_{q+1} (losing)					0.003***	0.002***
					(9.62)	(7.64)
$\log(\text{Mktcap}_q)$	0.011**	−0.004	−0.010*	0.024***	−0.002	−0.002
	(2.08)	(−0.71)	(−1.67)	(4.77)	(−0.39)	(−0.30)
$1/\text{Price}_q$	0.070***	0.072***	0.071***	0.079***	0.071***	0.078***
	(3.78)	(3.84)	(3.85)	(4.23)	(3.81)	(4.20)
$\log(\text{Book-to-market}_q)$	−0.044***	−0.054***	−0.053***	−0.043***	−0.051***	−0.050***
	(−4.61)	(−5.64)	(−5.54)	(−4.44)	(−5.38)	(−5.12)
Assets growth_{y-1}	0.070***	0.077***	0.076***	0.064***	0.076***	0.070***
	(5.87)	(6.52)	(6.44)	(5.28)	(6.35)	(5.80)
$\text{Profitability}_{y-1}$	−0.021	−0.039**	−0.040**	−0.027	−0.035**	−0.045***
	(−1.22)	(−2.28)	(−2.35)	(−1.62)	(−2.02)	(−2.72)
Past 6-month return	−0.049	−0.051*	−0.049	−0.052*	−0.050*	−0.053*
	(−1.64)	(−1.71)	(−1.65)	(−1.75)	(−1.69)	(−1.79)
Amihud ratio_q	−0.093***	−0.092***	−0.092***	−0.089***	−0.092***	−0.088***
	(−8.09)	(−8.07)	(−8.09)	(−7.90)	(−8.12)	(−7.97)
Beta_q	0.299***	0.297***	0.295***	0.294***	0.297***	0.291***
	(19.32)	(19.36)	(19.33)	(19.34)	(19.35)	(19.32)
Observations	355,484	355,484	355,484	355,484	355,484	355,484
R-squared	0.207	0.208	0.210	0.210	0.208	0.213

Table 4. Comparison of Ownership Measures

The table reports quarterly Fama and MacBeth (1973) regressions of market betas on the model-implied exposure (from Equation 12 in Section 3), the number of 13F institutional owners (NIO), the total 13F ownership, and the Herfindahl-Hirschman index of 13F institutional ownership (HHI). I include ordinary common shares (CRSP share codes of 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes of 1, 2, or 3). I exclude stocks with zero 13F institutional ownership or/and negative book value from Compustat. The market betas are computed by regressing daily stock returns in excess of the risk-free rates on contemporaneous and lagged value-weighted market returns in excess of the risk-free rates. The dependent variable is the sum of the two estimated coefficients. The main independent variables are the percentile rank of the model-implied exposure, the number of 13F institutional owners (NIO), the total 13F institutional ownership, and the Herfindahl-Hirschman index of 13F institutional ownership (HHI). Mktcap is the quarter-end market capitalization; Price is the quarter-end stock price; and Book-to-market is book equity divided by market equity. Assets growth is the change in assets scaled by lagged assets (Fama and French, 2015; Hou et al., 2015). Profitability is revenue minus the cost of goods sold scaled by total assets (Novy-Marx, 2013). Past-6-month return is the natural logarithm of cumulative past-6-month returns excluding the most recent month return, and the Amihud ratio is computed within each quarter following Amihud (2002). t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Beta_{q+1}					
	(1)	(2)	(3)	(4)	(5)	(6)
Rank: Model-implied exposure$_q$	0.007***				0.002***	
	(18.46)				(4.42)	
Rank: NIO$_q$		0.008***				0.006***
		(19.19)				(11.60)
Rank: 13F ownership$_q$			0.003***		0.002***	0.001***
			(21.88)		(11.37)	(5.61)
Rank: HHI$_q$				−0.004***	−0.002***	−0.000
				(−18.89)	(−11.82)	(−1.60)
log(mktcap$_q$)	−0.049***	−0.060***	0.017***	0.003	−0.022***	−0.053***
	(−8.57)	(−9.61)	(4.83)	(0.95)	(−3.66)	(−7.97)
1/Price$_q$	0.043***	0.027**	0.052***	0.043***	0.051***	0.035***
	(3.87)	(2.41)	(4.63)	(3.81)	(4.49)	(3.08)
log(book-to-market$_q$)	−0.074***	−0.080***	−0.069***	−0.066***	−0.074***	−0.079***
	(−10.13)	(−10.91)	(−9.70)	(−9.27)	(−10.20)	(−10.88)
Assets growth$_{y-1}$	0.100***	0.106***	0.096***	0.091***	0.095***	0.104***
	(10.70)	(11.77)	(10.28)	(9.66)	(10.03)	(11.79)
Profitability$_{y-1}$	−0.004	−0.012	−0.011	0.004	−0.019	−0.018
	(−0.37)	(−0.99)	(−0.90)	(0.30)	(−1.61)	(−1.53)
Past 6-month return	−0.026	0.005	−0.025	−0.023	−0.021	0.002
	(−1.23)	(0.23)	(−1.20)	(−1.09)	(−1.01)	(0.09)
Amihud ratio$_q$	−0.053***	−0.050***	−0.049***	−0.052***	−0.048***	−0.047***
	(−7.23)	(−7.03)	(−7.17)	(−7.22)	(−7.25)	(−7.06)
Beta$_q$	0.237***	0.230***	0.238***	0.239***	0.233***	0.228***
	(20.93)	(20.77)	(20.91)	(20.77)	(20.72)	(20.77)
Observations	624,867	624,867	624,867	624,867	624,867	624,867
R-squared	0.173	0.177	0.173	0.172	0.177	0.179

Table 5. Regression Discontinuity Approach

The table reports stock-quarter-level regression results of market beta on the number of active funds following a fuzzy regression discontinuity approach. The sample period spans the Russell reconstitution events between 2000 and 2006. In Panel A, the dependent variable is the number of active funds following the reconstitution events. Treatment is a dummy variable that equals one if a stock is expected to be included in the Russell 1000 index in June based on its May market capitalization ranking. In Panel B, the dependent variable is market beta. In each quarter, I regress each stock's daily returns in excess of the risk-free rates on contemporaneous and one-day-lagged CRSP value-weighted returns in excess of the risk-free rates and estimate slopes on the contemporaneous and lagged market returns. I compute beta as the sum of these two slopes. In Panel B, I use Treatment in Panel A as an instrumental variable for the number of active funds following the reconstitution events. I use the same set of control variables as in Table 2, and further control for changes in active and passive ownership following the reconstitution events. I report results using different bandwidths around the cutoff (50, 75, 100, and 125 ranks). I control for the third degree of polynomials of the ranking variable as well as their interaction terms with Treatment. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered by stock.

Panel A: First Stage				
Dependent variable:	Number of active funds			
Treatment	72.90***	61.29***	50.32***	52.67***
	(2.92)	(2.75)	(2.62)	(3.20)
RD bandwidth	50	75	100	125
RD controls	Cubic	Cubic	Cubic	Cubic
Time FE	Yes	Yes	Yes	Yes
Observations	2,402	3,578	4,711	5,890
R-squared	0.301	0.307	0.307	0.314
Panel B: Second Stage				
Dependent variable:	Beta			
Number of active funds (IV)	0.008*	0.009**	0.010**	0.012**
	(1.90)	(2.17)	(2.16)	(2.08)
RD bandwidth	50	75	100	125
RD controls	Cubic	Cubic	Cubic	Cubic
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	2,402	3,578	4,711	5,890

Table 6. Return Predictability

The table shows quarterly Fama and MacBeth (1973) regressions of stock returns on the model-implied exposure (from Equation 12 in Section 3) and the number of 13F institutional owners (NIO). I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership. The dependent variable is the natural logarithm of cumulative stock returns computed within each quarter. The main independent variables are the log or the percentile rank of the model-implied exposure, the number of 13F institutional owners (NIO), the number of active funds, and the number of passive funds. The changes in NIO and the number of funds are defined following Chen et al. (2002) and are ranked in each quarter. Mktcap is the quarter-end market capitalization; Book-to-market is book equity divided by market equity; and Assets growth is the change in assets scaled by lagged assets (Fama and French, 2015; Hou et al., 2015). Profitability is revenue minus the cost of goods sold, scaled by total assets (Novy-Marx, 2013). Past-6-month return is the natural logarithm of cumulative past-6-month returns excluding the most recent month return. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Return$_{q+1}$					
Sample period:	1980-2020	1980-2020	1980-2020	1997-2020	1980-2020	1997-2020
log(Model-implied exposure$_q$)	0.226**					
	(2.33)					
log(NIO$_q$)		1.337***				
		(3.84)				
Rank: Model-implied exposure$_q$			0.070***	0.079***		
			(4.27)	(2.85)		
Rank: NIO$_q$					0.063***	
					(3.78)	
Rank: NIO$_q$ (active)						0.079***
						(3.35)
Rank: NIO$_q$ (passive)						−0.019
						(−1.33)
Rank: ΔNIO$_q$			0.010***	0.007	0.009***	
			(3.07)	(1.32)	(2.73)	
Rank: ΔNIO$_q$ (active)						0.007
						(1.32)
Rank: ΔNIO$_q$ (passive)						−0.005
						(−1.29)
log(Mktcap$_q$)	−0.628***	−1.139***	−1.179***	−1.389***	−1.119***	−1.220***
	(−3.12)	(−3.66)	(−4.53)	(−3.45)	(−3.75)	(−3.12)
log(Book-to-market$_q$)	0.880***	0.750***	0.845***	0.426	0.808***	0.329
	(3.48)	(2.90)	(3.35)	(1.16)	(3.24)	(0.92)
Assets growth$_{y-1}$	−0.733***	−0.681***	−0.731***	−0.637***	−0.708***	−0.622***
	(−5.11)	(−5.01)	(−5.21)	(−3.18)	(−5.26)	(−3.41)
Profitability$_{y-1}$	2.124***	1.931***	1.980***	1.474**	1.953***	1.380**
	(5.52)	(5.03)	(5.09)	(2.56)	(5.03)	(2.38)
Past 6-month return	0.017***	0.020***	0.015**	−0.002	0.019***	0.001
	(2.69)	(3.67)	(2.47)	(−0.21)	(3.37)	(0.14)
Observations	613,312	618,521	613,312	337,807	618,521	337,807
R-squared	0.039	0.041	0.040	0.036	0.042	0.040

Table 7. Returns and Betas of Portfolios

The table reports the average value-weighted monthly returns and the CAPM alphas and betas of portfolios. I include ordinary common shares (CRSP share codes 10 or 11) traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership. In Panel A, I form 10 portfolios by sorting stocks on the model-implied exposure (from Equation 12 in Section 3). In Panel B, I form 10 portfolios by sorting stocks on Residual NIO. Specifically, I regress the natural logarithm of 1 + NIO on the natural logarithm of market capitalization each month and form 10 portfolios in the next month based on the residuals. The portfolios are rebalanced monthly. Return is the time-series average of the value-weighted monthly portfolio returns. CAPM alphas and betas are estimated using the CAPM model (Sharpe, 1964; Lintner, 1965; Mossin, 1966). Returns and alphas are show in percentages. t-statistics are adjusted for heteroscedasticity and autocorrelations.

Panel A: Portfolios Sorted by Model-implied Exposure

Deciles	L	2	3	4	5	6	7	8	9	H	H−L
Return	0.52	0.59	0.69	0.92	0.71	0.83	0.89	1.03	1.00	1.09	0.57
t(Return)	2.23	2.05	2.30	3.36	2.92	3.56	4.15	4.89	4.47	4.43	2.91
CAPM α	−0.27	−0.36	−0.36	−0.04	−0.27	−0.15	−0.06	0.07	0.00	0.04	0.31
t(CAPM α)	−1.56	−1.94	−2.03	−0.21	−2.33	−1.38	−0.74	1.17	0.06	0.46	1.61
CAPM β	0.73	0.95	1.12	0.97	1.02	1.01	0.97	0.99	1.04	1.12	0.39

Panel B: Portfolios Sorted by Residual NIO

Deciles	L	2	3	4	5	6	7	8	9	H	H−L
Return	0.89	0.99	1.00	1.18	1.04	1.13	1.09	1.18	1.34	1.60	0.71
t(Return)	3.51	4.15	4.67	5.29	5.01	5.36	5.10	5.30	5.22	4.84	2.09
CAPM α	−0.09	0.00	0.01	0.16	0.01	0.08	0.02	0.05	0.13	0.27	0.35
t(CAPM α)	−0.69	−0.01	0.19	2.64	0.18	0.98	0.24	0.46	0.80	1.02	1.04
CAPM β	0.93	0.94	0.94	0.99	0.99	1.01	1.04	1.14	1.25	1.44	0.52

Table 8. The Covariance Channel

The table reports the estimation results of Equation 17 and the average value-weighted monthly returns of portfolios based on the model-implied exposure (Panels A and C) and Residual NIO (Panels B and D). The portfolio formations are described in Table 7. Panels A and B report the parameter estimates from Equation 17 and the test results of the null hypotheses $H_0 : \Gamma_\alpha = 0$ and $H_0 : \Gamma_\beta = 0$. The p-values are calculated from bootstrapped statistics following Kelly et al. (2019). Panels C and D report the portfolio returns during the stock market crash months defined as months in which CRSP value-weighted market returns in excess of the risk-free rates are ranked in the bottom 10%. Ret−Mkt is the time-series average of monthly portfolio returns in excess of stock market returns. CAPM α is the time-series average of monthly portfolio returns in excess of risk-free rates minus CAPM β multiplied by market excess returns. The CAPM βs are estimated on a rolling basis using the past-60-month observations. Returns and alphas are shown in percentages.

Panel A: Estimation Results (Model-implied Exposure)				
Γ_α	Γ_β	R^2	$H_0 : \Gamma_\alpha = 0$ (p-value)	$H_0 : \Gamma_\beta = 0$ (p-value)
0.003	0.125	0.742	0.660	0.054
Panel B: Estimation Results (Residual NIO)				
Γ_α	Γ_β	R^2	$H_0 : \Gamma_\alpha = 0$ (p-value)	$H_0 : \Gamma_\beta = 0$ (p-value)
0.001	0.189	0.803	0.574	0.003

Panel C: Price Crashes in Bad Times (Model-implied Exposure)											
Deciles	L	2	3	4	5	6	7	8	9	H	H−L
Ret−Mkt	2.26	−0.52	−1.98	0.11	−0.96	−0.88	0.06	0.07	−0.39	−0.55	−2.81
t(Ret−Mkt)	3.11	−0.75	−2.30	0.13	−1.72	−1.45	0.18	0.26	−1.39	−1.52	−3.84
CAPM α	0.14	−0.33	−0.66	0.06	−0.56	−0.79	−0.20	0.05	−0.13	0.46	0.32
t(CAPM α)	0.20	−0.49	−0.78	0.07	−1.00	−1.31	−0.62	0.22	−0.46	1.31	0.44
CAPM β	0.74	1.03	1.17	0.99	1.06	1.01	0.97	1.00	1.03	1.12	0.38
Panel D: Price Crashes in Bad Times (Residual NIO)											
Deciles	L	2	3	4	5	6	7	8	9	H	H−L
Ret−Mkt	0.42	0.48	0.67	0.27	0.41	0.07	−0.02	−0.84	−1.68	−3.08	−3.50
t(Ret−Mkt)	0.78	1.39	2.63	0.92	1.32	0.23	−0.06	−1.81	−3.05	−4.63	−3.33
CAPM α	0.08	0.28	−0.08	0.16	0.30	0.18	0.25	0.26	0.20	−0.03	−0.11
t(CAPM α)	0.13	0.83	−0.26	0.53	1.03	0.63	0.68	0.55	0.36	−0.04	−0.10
CAPM β	0.97	0.98	0.91	0.98	0.99	1.01	1.04	1.14	1.24	1.39	0.43

Appendix A Data Sources

A.1 13F Institutional Ownership Data

I obtain 13F institutional ownership information from the Thomson Reuters Financial database (S34 dataset). The sample period spans 1980 Q2 to 2020 Q2. I merge securities with data from CRSP using their historical CUSIP.

A.2 Fund-level Data

I obtain fund-level holdings information of 13F institutional investors and mutual funds (S12 dataset) from the Thomson Reuters Global Mutual Fund Ownership database. The sample period spans 1997 Q2 to 2020 Q2. I merge securities with CRSP data using their historical CUSIP. I include U.S. funds and drop finance companies, foundations, private equity and venture capital, sovereign wealth funds, research firms, strategic entities, corporations, holding companies, individual investors, and government agents as identified by the owner type code. I classify funds as active or passive, relying on the owner orientation code.

I obtain information on returns and cash holdings for mutual funds from the CRSP Survivor-Bias-Free Mutual Fund Database and merge these data with the mutual-fund stock-holdings data using the MFLINKS file from WRDS.

A.3 Factor Data

The capital asset pricing model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), and the Fama-French-Carhart six-factor model (Fama and French, 2018) factors are from Kenneth French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`. The Hou-Mo-Xue-Zhang q^5 factor model (Hou et al., 2015; Hou, Mo, Xue, and

Zhang, 2021) factors are from the q-factor data library website: `https://global-q.org/index.html`.

Appendix B Variable Definitions

Variable	Definition	Source
Number of institutional owners (NIO)	The number of 13F institutional owners for stock in each quarter.	Thomson Reuters
13F ownership	The total 13F institutional ownership for stock in each quarter.	Thomson Reuters
HHI	The Herfindahl-Hirschman index of 13F institutional ownership in each quarter.	Thomson Reuters
Number of active funds	The number of active fund owners for stock in each quarter based on the owner orientation code.	Thomson Reuters Global
Active fund ownership	The total active fund ownership for stock in each quarter.	Thomson Reuters Global
Number of passive funds	The number of passive fund owners for stock in each quarter based on the owner orientation code.	Thomson Reuters Global
Passive fund ownership	The total passive fund ownership for stock in each quarter.	Thomson Reuters Global
Beta	The sum of stocks' coefficients on contemporaneous and lagged CRSP value-weighted returns using daily returns within each quarter.	CRSP
Idiosyncratic volatility	The standard deviation of the residuals from the CAPM model using daily returns within each quarter.	CRSP
Mktcap	The quarter-end stock market capitalization.	CRSP
Price	The quarter-end stock price.	CRSP
Past-6-month return	The cumulative past-6-month returns excluding the most recent month return.	CRSP
Amihud ratio	The quarterly average of absolute daily returns scaled by the daily dollar volume in $ million.	CRSP
Book-to-market	The quarterly book-to-market ratio, computed as book equity divided by market equity.	CRSP, Compustat
Assets growth	Changes in total assets scaled by lagged total assets.	Compustat
Operating profitability	Revenue minus the cost of goods sold, scaled by total assets.	Compustat

Appendix C General Equilibrium

The model presented in Section 3 takes the exogenously specified functional form of institutional investors' demand shocks as given. This section shows that the key economic mechanism prevails in a more realistic model, building on the general equilibrium framework of Basak and Pavlova (2013). In this framework, institutional investors' demand shocks arise endogenously due to their concern about their performance relative to a similar market index.

C.1 Economic Setup

Following Basak and Pavlova (2013), I consider a pure exchange market economy that evolves in continuous time. There is a representative retail investor and H institutional investors, indexed by $h = 1, ..., H$. There is a risk-free bond, N risky stocks, and N sources of risk, specified by a standard N-dimensional Brownian motion $\boldsymbol{\omega} = (\omega_1, ..., \omega_N)^\intercal$. For $j = 1, ..., N$, I assume that the stock price, S_{jt}, follows the dynamics given by

$$dS_{jt} = S_{jt}\Big[\mu_{S_{jt}} dt + \boldsymbol{\sigma}_{S_{jt}} d\boldsymbol{\omega_t}\Big], \tag{C.1}$$

where the vector of stock mean returns is $\boldsymbol{\mu}_{S_t} = (\mu_{S_{1t}}, ..., \mu_{S_{Nt}})^\intercal$ and the stock volatility matrix is $\boldsymbol{\sigma}_{S_t} = \{\sigma_{S_{jkt}};\ j, k = 1, ..., N\}$. Note that the stock returns and volatility are endogenously determined in equilibrium. The risk-free bond is in zero net supply and pays a zero interest rate without loss of generality. The value of the stock market portfolio, $S_{MKT,\ t}$, is the sum of the stock prices given by

$$S_{MKT,\ t} = \sum_{j=1}^{N} S_{jt}, \tag{C.2}$$

with assumed dynamics given by

$$dS_{MKT,\ t} = S_{MKT,\ t}\big[\mu_{MKT,\ t}dt + \boldsymbol{\sigma}_{MKT,\ t}d\boldsymbol{\omega_t}\big]. \tag{C.3}$$

Institutional investors, indexed by $h = 1, ..., H$, are given a distinct investment universe, a set of stocks they are allowed to hold. In this economy, institutions are only allowed to trade stocks included in their investment universe.[23] There are H index portfolios, and each index consists of stocks that comprise the investment universe of each institution. To be specific, consider H natural numbers, M_1, ..., M_H, where $0 < M_1 < M_2 < ... < M_H < N$. (Recall that N is the total number of stocks in the economy.) The first index consists of the first M_1 stocks that comprise the investment universe of the first institution ($h = 1$); $\mathcal{M}_1 = \{S_1, ..., S_{M_1}\}$, the second index consists of the first M_2 stocks that comprise the investment universe of the second institution ($h = 2$); $\mathcal{M}_2 = \{S_1, ..., S_{M_2}\}$, ..., and the H^{th} index consists of the first M_H stocks that comprise the investment universe of the last institution ($h = H$); $\mathcal{M}_H = \{S_1, ..., S_{M_H}\}$. Note that the first M_1 stocks, $\{S_{1t}, ..., S_{M_1}\}$, belong to the investment universe of all institutional investors. The last $N - M_H$ stocks, $\{S_{M_H+1}, ..., S_N\}$, do not belong to any investment universe of institutional investors. The degree to which the remaining stocks belong to institutions' investment universe lies between the two extreme cases. The value of the indexes, denoted as $S_t^1, ..., S_t^H$, is the sum of the stock prices in the index given by

$$S_t^h = \sum_{j=1}^{M_h} S_{jt}. \tag{C.4}$$

Each stock is in positive net supply, and its terminal payoff (or dividend) D_{jT}, due at time T, follows the process given by

$$dD_{jt} = D_{jt}\boldsymbol{\sigma}_j d\boldsymbol{\omega}_t, \tag{C.5}$$

[23] As discussed earlier, the investment universe of institutional investors does not need to be completely restrictive. For simplicity, however, I assume that institutions face strict constraints.

where $\boldsymbol{\sigma}_j > 0$ is the constant N-dimensional vector. The process D_{jt} represents the cash flow news about the terminal stock dividend D_{jT}. Therefore, D_{jT} equals the stock price at time T (i.e., $S_{jT} = D_{jT}$). For tractability, I assume that the stocks' fundamentals (dividends) are independent. That is, only the j^{th} element of $\boldsymbol{\sigma}_j$ is nonzero. This implies $\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_k = 0$ for all $j \neq k$. Importantly, I assume that the last stocks of each index and the stock market portfolio (i.e., S_{M_1}, S_{M_2}, ..., S_{M_H}, S_N) do not follow the process in Equation (C.5). In what follows, I specify processes for the sums of all stocks in the indexes and the stock market. This modeling device is taken from Basak and Pavlova (2013), which in turn is inspired by Menzly, Santos, and Veronesi (2004). It allows one to assume that the cash flow news of the indexes and the stock market portfolio follow geometric Brownian motion processes (as in Equations (C.6) and (C.7)), which improves the tractability of the model considerably.

The stock market has a terminal payoff $S_{MKT,\ t} = D_T$, determined by the process

$$dD_t = D_t \boldsymbol{\sigma} d\boldsymbol{\omega}_t, \tag{C.6}$$

where $\boldsymbol{\sigma} > 0$ is the constant N-dimensional vector. Each index has the terminal payoff I_T^h, due at time T, determined by the process

$$dI_t^h = I_t^h \boldsymbol{\sigma}_h d\boldsymbol{\omega}_t, \tag{C.7}$$

where $\boldsymbol{\sigma}_h > 0$ is the constant N-dimensional vector with the first M_h non-zero components and the remaining zero components. Therefore, stocks that comprise the index S_t^h are positively correlated with the index in terms of the cash flow news, while stocks that are not a member of the index S_t^h have zero correlations with the index. That is, $\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h > 0$ for $j = 1, ..., M_h$, while $\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h = 0$ for $j = M_h + 1, ..., N$.

Each type of investor (indexed by $i = 1, ..., H, R$) dynamically chooses a multidimensional portfolio process $\boldsymbol{\phi}_i$, where R refers to the retail investor and $\boldsymbol{\phi}_i = (\phi_{i1}, ..., \phi_{iN})^\intercal$ represents the portfolio weights in each stock. The retail investor can invest in all N stocks. However, the institutions are only allowed to hold stocks included in their investment universe; $\mathcal{M}_1, ..., \mathcal{M}_H$. The portfolio value of each investor W_{it} follows the dynamics given by

$$dW_{Rt} = W_{Rt}\boldsymbol{\phi}_{Rt}^{\intercal}\left[\boldsymbol{\mu}_{S_t}dt + \boldsymbol{\sigma}_{S_t}d\boldsymbol{\omega}_t\right] \tag{C.8}$$

$$dW_{ht} = W_{ht}\boldsymbol{\phi}_{ht}^{\intercal}\left[\boldsymbol{\mu}_{S_t}^{h}dt + \boldsymbol{\sigma}_{S_t}^{h}d\boldsymbol{\omega}_t^{h}\right], \tag{C.9}$$

where R refers to the retail investor and $h = 1, ..., H$. In addition, the term $\boldsymbol{\phi}_{ht}$ is the $|\mathcal{M}_h|$-dimensional vector; the term $\boldsymbol{\mu}_{S_t}^{h}$ is the $|\mathcal{M}_h|$-dimensional subvector of $\boldsymbol{\mu}_{S_t}$ that consists of the drift terms of the stocks that comprise the investment universe of institution h; the term $\boldsymbol{\sigma}_{S_t}^{h}$ is the $|\mathcal{M}_h|$-dimensional submatrix of $\boldsymbol{\sigma}_{S_t}$ that consists of the diffusion terms of the stocks that comprise the investment universe of institution h; and the term $\boldsymbol{\omega}_t^{h}$ is the $|\mathcal{M}_h|$-dimensional subvector of $\boldsymbol{\omega}_t$, which consists of the risk components of the stocks that comprise the investment universe of institution h.

Each institution is initially endowed with λ^h fraction of the stock market and, thus, has initial assets worth $W_{h0} = \lambda^h S_{MKT,\,0}$, where $\sum_{i=1}^{H}\lambda^h = \lambda$. As discussed earlier, I assume that institutional investors are concerned about their performance relative to the overall stock market. Under the Basak and Pavlova (2013) framework, the correct formalization of this assumption would be to set each institution's objective function as $u_h(W_{hT}) = (1 + bS_T)log(W_{hT})$. Unfortunately, this specification does not allow me to drive closed-form solutions. For tractability, I instead set the objective function of each institution as

$$u_h(W_{hT}) = (1 + bS_T^{h})log(W_{hT}), \tag{C.10}$$

where $b > 0$ and S_T^h is the terminal value of the index that consists of the stocks that comprise the investment universe of institution h. With this approach, each institution perceives the stock market performance through the lens of its index portfolio performance, which is correlated with the overall stock market. This modeling device enables me to model institutional investors' concerns about relative performance evaluation while delivering exact closed-form solutions.[24]

The representative retail investor is initially endowed with $1 - \lambda$ fraction of the stock market and therefore has initial assets worth $W_{R0} = (1-\lambda)S_{MKT,\,0}$. The objective function of the retail investor is the standard logarithmic utility function: $u_R(W_{RT}) = log(W_{RT})$.

C.2 Portfolio Choice

Lemma 1 shows the investors' optimal portfolios in closed-form.

Lemma 1. *The retail and institutional investors' optimal portfolio processes are given by*

$$\begin{aligned} \boldsymbol{\phi}_{Rt} &= \left(\boldsymbol{\sigma}_{S_t}[\boldsymbol{\sigma}_{S_t}]^\intercal\right)^{-1}\boldsymbol{\mu}_{S_t} \\ \boldsymbol{\phi}_{ht} &= \left(\boldsymbol{\sigma}^h_{S_t}[\boldsymbol{\sigma}^h_{S_t}]^\intercal\right)^{-1}\boldsymbol{\mu}^h_{S_t} + \frac{bI^h_t}{1+bI^h_t}\left([\boldsymbol{\sigma}^h_{S_t}]^\intercal\right)^{-1}\boldsymbol{\sigma}^h_h, \end{aligned} \tag{C.11}$$

where $\boldsymbol{\sigma}^h_h > 0$ is the $|\mathcal{M}_h|$-dimensional subvector of $\boldsymbol{\sigma}_h$ that consists of the first M_h non-zero components.

The optimal portfolio of the representative retail investor is the standard mean-variance efficient portfolio. On the other hand, each institution holds the mean-variance efficient portfolio (per its investment universe) plus an additional portfolio that is positively correlated with the aggregate cash flow news. (Recall that I^h_t is positively correlated with the market-wide cash flow news, D_t.)

Following good cash flow news, the marginal utility of wealth increases among institutional investors, dictated by their objective functions in Equation (C.10). Intuitively, institutional investors seek to post a higher return in order not to fall behind when the stock

[24] Each index could also be thought of as a benchmark index. An alternative interpretation is that institutional managers strive to perform well when their benchmarks are outperforming. However, institutions' investment mandates are usually not publicly disclosed; thus, benchmark information is difficult to obtain. The exception is the mutual fund industry. There are 14 benchmarks that account for 90% of the mutual fund industry's assets under management: S&P 500, CRSP US Total Market, Russell 1000 Growth, Russell 1000 Value, Russell 2000, Russell Mid Cap Growth, Russell Mid Cap Value, Russell 3000 Growth, Russell 3000, Russell 2000 Value, Russell 2000 Growth, Russell 1000, Russell 3000 Value, and Russell Mid Cap.

market is performing well. They do so by increasing their portfolio exposure to the stock market by demanding more stocks that comprise their investment universe (i.e., increase the riskiness of their portfolios). Note that institutional investors take on more (less) risk during bull (bear) markets. That is, the effective risk appetite of institutional investors is procyclical according to their optimal portfolio choices in Equation (C.11).

Proof. See Appendix D.

C.3 Price

Equilibrium in this economy is standard. Equilibrium portfolios and asset prices are such that (i) retail and institutional investors maximize their objective functions, and (ii) financial markets clear. Note that the wealth of investors and asset prices are simultaneously determined in this economy.

Proposition 1 reports the equilibrium stock prices in closed-form.

Proposition 1. *The equilibrium prices of the market portfolio, $S_{MKT,\ t}$; the stocks that are a member of some index portfolios, S_{jt}; and the stocks that are not a member of any index portfolios, S_{kt}, are given by*

$$S_{MKT\ t} = \bar{S}_{MKT,\ t} \frac{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}(I_t^h - I_0^h)}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}(e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h - I_0^h)}$$

$$S_{jt} = \bar{S}_{jt} \frac{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}(e^{(-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma} + \boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h)(T-t)} I_t^h - I_0^h)}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}(e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h - I_0^h)} \tag{C.12}$$

$$S_{kt} = \bar{S}_{kt},$$

where $\bar{S}_{MKT\ t}$, $\bar{S}_{jt}$, and $\bar{S}_{kt}$ are the equilibrium prices of the market portfolio, the stocks that are a member of some index portfolios, and the stocks that are not a member of any index portfolios, respectively, in the benchmark economy with no institutions given by

$$\bar{S}_{MKT\ t} = e^{-\|\boldsymbol{\sigma}\|^2(T-t)} D_t, \quad \bar{S}_{jt} = e^{-\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}(T-t)} D_{jt}, \quad \bar{S}_{kt} = e^{-\boldsymbol{\sigma}_k^\intercal \boldsymbol{\sigma}(T-t)} D_{kt} \tag{C.13}$$

Equation (C.12) shows that the price levels of the stock market and the stocks that compose some index portfolios increase in the presence of institutions (i.e., $\lambda^h > 0$). This is simply a wealth effect as in Kyle and Xiong (2001), yet the effect becomes stronger as institutions' effective risk appetite becomes an increasing function of the level of cash flow news according to their optimal portfolio choices. Because institutional managers increase their portfolios' exposure to the stock market, they benefit substantially more from good cash flow news. As they become wealthier and their effective risk appetite increases, institutional investors' demand for stocks increases. Since stocks are in fixed supply and institutions want to buy more, the stock prices should be higher in equilibrium.

Note that the term $\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h$ in the second line of Equation (C.12) is non-zero only if stock j comprises index h (i.e., if stock j is included in the investment universe of institution h). Therefore, a stock included in the investment universe of more institutional investors exhibits a higher price level as it faces greater demand by more institutional investors. Recall that institutional investors are only allowed to hold stocks included in their investment universe. Therefore, a stock with a higher number of institutional owners (i.e., high NIO) exhibits a higher price level in equilibrium.

Proof. See Appendix D.

C.4 Volatility

Proposition 2 reports the equilibrium stock return volatility in closed-form.

Proposition 2. *The equilibrium return volatility of the market portfolio, $\boldsymbol{\sigma}_{MKT,\ t}$; the stocks that are a member of some index portfolios, $\boldsymbol{\sigma}_{jt}$; and the stocks that are not a member of any index portfolios, $\boldsymbol{\sigma}_{kt}$, are given by*

$$\boldsymbol{\sigma}_{MKT,\ t} = \bar{\boldsymbol{\sigma}}_{MKT\ t} + \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} \left[1 + X - \beta_h \Big(1+Y\Big)\right] I_t^h \boldsymbol{\sigma}_h}{\Big(1+X\Big)\Big(1+Y\Big)}$$

$$\boldsymbol{\sigma}_{jt} = \bar{\boldsymbol{\sigma}}_{jt} + \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} \left[e^{\boldsymbol{\sigma}_j^{\intercal}\boldsymbol{\sigma}_h(T-t)} \Big(1+X\Big) - \Big(1+\gamma_j\Big)\right] \beta_h I_t^h \boldsymbol{\sigma}_h}{\Big(1+\gamma_j\Big)\Big(1+X\Big)} \tag{C.14}$$

$$\boldsymbol{\sigma}_{kt} = \bar{\boldsymbol{\sigma}}_{kt},$$

where $\bar{\boldsymbol{\sigma}}_{MKT\ t}$*,* $\bar{\boldsymbol{\sigma}}_{jt}$*, and* $\bar{\boldsymbol{\sigma}}_{kt}$ *are the equilibrium return volatility of the market portfolio, the stocks that are a member of some index portfolios, and the stocks that are not a member of any index portfolios, respectively, in the benchmark economy with no institutions given by*

$$\bar{\boldsymbol{\sigma}}_{MKT,\ t} = \boldsymbol{\sigma}, \quad \bar{\boldsymbol{\sigma}}_{jt} = \boldsymbol{\sigma}_j, \quad \bar{\boldsymbol{\sigma}}_{kt} = \boldsymbol{\sigma}_k. \tag{C.15}$$

β_h*,* γ_j*,* X*, and* Y *are given by*

$$\beta_h = e^{-\boldsymbol{\sigma}_h^{\intercal}\boldsymbol{\sigma}(T-t)}, \qquad \gamma_j = \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} \Big(\beta_h e^{\boldsymbol{\sigma}_j^{\intercal}\boldsymbol{\sigma}_h(T-t)} I_t^h - I_0^h\Big)$$
$$X = \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} \Big(\beta_h I_t^h - I_0^h\Big), \qquad Y = \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} \Big(I_t^h - I_0^h\Big).$$

Equation (C.14) shows that stock market volatility increases in the presence of institutions (i.e., $\lambda^h > 0$). Since institutional investors increase their portfolios' exposure to the stock market, they earn (lose) substantially more from good (bad) cash flow news in the stock market and thus their demand for stocks increases (decreases) as they get wealthier (poorer). The procyclical nature of institutional investors' effective risk appetite in Equation (C.11) magnifies the portfolio rebalancing behavior. Since stocks are in fixed supply but institutional investors "excessively" buy or sell stocks, depending on the sign of the cash flow news, the stock prices fluctuate substantially. In other words, the portfolio rebalancing of institutional investors amplifies the cash flow news of the economy, increasing the volatility of the stock market in equilibrium.

Note that the term $\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h$ in the second line of Equation (C.14) is non-zero only if stock j is included in index h (i.e., if stock j is included in the investment universe of institution h). Therefore, a stock included in the investment universe of more institutional investors exhibits higher volatility. This increase in volatility occurs because institutional investors' amplification of cash flow news only affects stocks included in their investment universe. As such, a stock with a higher number of institutional owners (i.e., high NIO) exhibits higher volatility in equilibrium. Panel (a) of Appendix Figure A.I graphically illustrates the relationship between NIO and the equilibrium volatility. Panel (b) shows the relationship between NIO and the equilibrium market betas.[25]

Proof. See Appendix D.

C.5 Sharpe Ratio

Proposition 3 reports the equilibrium Sharpe ratios in closed-form.

Proposition 3. *The equilibrium Sharpe ratios of the stocks are given by*

$$\boldsymbol{\kappa}_t = \boldsymbol{\sigma} - \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h \boldsymbol{\sigma_h}}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} \left(e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h - I_0^h \right)}. \tag{C.16}$$

Equation (C.16) shows that the Sharpe ratios of the stocks decrease in the presence of institutions (i.e., $\lambda^h > 0$). Recall that $\boldsymbol{\sigma}_h$ is the N-dimensional vector with the first M_h positive components and the remaining zero components. (Recall that M_H denotes the number of stocks in index h.) Therefore, a stock's Sharpe ratio decreases more if it is included in the investment universe of more institutional investors. For example, the first component of $\boldsymbol{\kappa}_t$, which is the Sharpe ratio of the stock included in the investment universe of all institutional investors, is smaller than the remaining components since the

[25] The equilibrium market beta of stock j is computed as $\boldsymbol{\sigma}_{jt}^\intercal \boldsymbol{\sigma}_{jt} / [\boldsymbol{\sigma}_{MKT,\ t}]^\intercal [\boldsymbol{\sigma}_{MKT,\ t}]$.

first component of $\boldsymbol{\sigma}_h$ (i.e., see the vector $\boldsymbol{\sigma}_h$ next to I_t^h in the numerator) is positive for all $h = 1, ..., H$. As such, a stock with a higher number of institutional owners (i.e., high NIO) exhibits a lower Sharpe ratio in equilibrium. Panel (c) of Appendix Figure A.I graphically illustrates the relationship between NIO and the equilibrium Sharpe ratios.

Proof. See Appendix D.

C.6 Premium

In the model, it is unclear whether the high NIO stocks command a premium. Under no arbitrage, the premium in equilibrium can be expressed as $\boldsymbol{\mu}_{S_t} = \boldsymbol{\sigma}_{S_t}^{\intercal} \boldsymbol{\kappa}_t$. Recall that the Sharpe ratio ($\boldsymbol{\kappa}_t$) decreases in NIO, while the volatility ($\boldsymbol{\sigma}_{S_t}$) increases in NIO. Therefore, the premium ($\boldsymbol{\mu}_{S_t}$) increases in NIO only if the the volatility effect dominates.

Intuitively, how dominant institutional investors are in the economy is important for determining the relationship between NIO and the equilibrium premium. Consider the following two extreme cases. In an economy with no mean-variance efficient investors, I find that institutional investors' demand for stocks becomes so strong that they are willing to hold stocks even when the Sharpe ratios are very low (i.e., low premium and high volatility). Therefore, in this economy, the premium decreases in NIO even though the volatility increases in NIO. On the other hand, in an economy with no institutional investors, every stock becomes identical in terms of price, volatility, Sharpe ratio, and premium.

Consequently, the presence of both mean-variance efficient investors and institutional investors is a necessary condition for the high NIO stocks to command a premium. This is because the former are the marginal players who require compensation for bearing "excessive" volatility as they dislike volatility the most, and without the latter, there is no volatility amplification. However, it is important to note that what happens, in reality, is likely that institutional investors dislike the increased volatility as much as other investors do. Therefore, the high NIO stocks would command a premium regardless of the presence of mean-variance efficient investors. In the model, with plausible parameter choices,[26] I find that the higher volatility can translate into a premium. Panel (d) of Appendix Figure A.I graphically illustrates the relationship between NIO and the equilibrium premium.

Overall, the theoretical framework replicates the empirical patterns in the data well. Institutional investors need to perform better than their benchmark indexes and face constraints on the set of stocks they are allowed to hold (i.e., investment universe). These two mechanisms create the cross-sectional variation in stock return volatility and market betas. Finally, the amplified systematic volatility is priced in the cross-section with plausible parameter choices.

Appendix D Proofs

D.1 Proof of Lemma 1

I assume a dynamically complete market with a riskless bond and N risky stocks. It is known that there exists a state price density process ξ such that the time-t value of payoff C_T is given by $\xi_t C_t = E_t[\xi_T C_T]$. The state price density process follows the dynamics given by

$$d\xi_t = -\xi_t \boldsymbol{\kappa}_t^{\intercal} d\boldsymbol{\omega}_t, \tag{D.1}$$

where $\boldsymbol{\kappa}_t = \boldsymbol{\mu}_{S_t}^{-1} \boldsymbol{\sigma}_{S_t}$ is the N-dimensional Sharpe ratio process. Investor i's dynamic budget constraint (C.8), (C.9) can be expressed as

[26] I calibrate the model as follows: There are $N = 50$ stocks, indexed by $j = 1, ..., 50$, and $H = 50$ benchmark index portfolios, indexed by $h = 1, ..., 50$. The first index includes the first stock, the second index includes the first and the second stocks, ..., and the last (50th) index includes all stocks. The parameter values are $\lambda = 0.3$, $b = 1$, $t = 1$, $T = 20$, and $I_0^h = 1$ for all h. In addition, $I_t^h = 1.25$ for all h, and $\boldsymbol{\sigma}_j = 0.3\boldsymbol{i}_j$ for all j, where $\boldsymbol{i}_j$ is an N-dimensional unit vector with the j^{th} element equal to 1 and the remaining values equal to 0. Further, $\boldsymbol{\sigma}_h = 0.3 \sum_{j=1}^{M_h} \boldsymbol{i}_j / \sqrt{M_h}$ for all h, where M_h is the number of stocks in index h, and $\boldsymbol{\sigma} = 0.3 \sum_{j=1}^{N} \boldsymbol{i}_j \sqrt{N}$.

$$E_t[\xi_T W_{iT}] = \xi_t W_{it}. \tag{D.2}$$

Maximizing the institution's expected objective function (C.10) subject to (D.2) evaluated at time $t = 0$ yields the institution's optimal terminal wealth, given by

$$W_{hT} = \frac{1 + bI_T^h}{y_h \xi_T},$$

where $1/y_h$ solves (D.2) evaluated at $t = 0$. Since D_t is log-normally distributed for all t,

$$\frac{1}{y_h} = \frac{\lambda^h \xi_0 S_{MKT\ 0}}{1 + bI_0^h}.$$

Then, the institution's optimal terminal wealth is given by

$$W_{hT} = \frac{\lambda^h \xi_0 S_{MKT\ 0}}{\xi_T} \frac{1 + bI_T^h}{1 + bI_0^h}. \tag{D.3}$$

Combining (D.2) and (D.3), the institution's optimal time-t wealth can be expressed as

$$\xi_t W_{ht} = \lambda^h \xi_0 S_{MKT\ 0} \frac{1 + bI_t^h}{1 + bI_0^h}. \tag{D.4}$$

Applying Itô's lemma to both sides of (D.4), and using (C.8), (C.9) and (D.1), gives me

$$\xi_t W_{ht}(\boldsymbol{\phi}_{ht}^{\intercal} \boldsymbol{\sigma}_{S_t}^h - [\boldsymbol{\kappa}_t^h]^{\intercal}) d\boldsymbol{\omega}_t^h = \lambda^h \xi_0 S_{MKT\ 0} \frac{bI_t^h}{1 + bI_t^h} \boldsymbol{\sigma}_h d\boldsymbol{\omega}_t^h,$$

where $\boldsymbol{\kappa}_t^h$ is the $|\mathcal{M}_h|$-dimensional subvector of $\boldsymbol{\kappa}_t^{\intercal}$ that consists of the Sharpe ratios of the stocks included in the investment universe of institution h.

Matching the diffusion terms and rearranging gives the institution's optimal portfolio (C.11). Similarly, the retail investor's optimal terminal and time-T wealth are given by

$$W_{RT} = \frac{(1 - \lambda) \xi_0 S_{MKT\ 0}}{\xi_T} \tag{D.5}$$

$$\xi_t W_{Rt} = (1-\lambda)\xi_0 S_{MKT0}. \tag{D.6}$$

Applying Itô's lemma gives the retail investor's optimal portfolio (C.11). ■

D.2 Proof of Proposition 1

I first determine the equilibrium-state price-density process. Combining the market-clearing condition, $W_{1T} + ... + W_{HT} + W_{RT} = D_T$, (D.3), and (D.5), gives me

$$\xi_T = \frac{\xi_0 S_{MKT\ 0}}{D_T}\left[1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1 + bI_0^h}\left(I_T^h - I_0^h\right)\right]. \tag{D.7}$$

Using log-normal distributions $E_t[1/D_T] = e^{\|\boldsymbol{\sigma}\|^2(T-t)}/D_t$, $E_t[I_T^h/D_T] = e^{(\|\boldsymbol{\sigma}\|^2 - \boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma})(T-t)} I_t^h/D_t$, (D.7), and rearranging gives

$$\xi_t = \frac{\xi_0 S_{MKT\ 0}}{D_t} e^{\|\boldsymbol{\sigma}\|^2(T-t)}\left[1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1 + bI_0^h}\left(e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h - I_0^h\right)\right]. \tag{D.8}$$

Using (D.7) and after some manipulation, the equilibrium market portfolio price is given by

$$\begin{aligned} \xi_t S_{MKT\ t} &= E_t[\xi_T D_T] \\ &= \xi_0 S_{MKT\ 0} E_t\left[1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1 + bI_0^h}\left(I_t^h - I_0^h\right)\right]. \end{aligned} \tag{D.9}$$

Combining (D.8) and (D.9) gives the equilibrium market portfolio price in (C.12). The price in the benchmark economy without institutions is obtained by setting $b = 0$.

Using (D.7) and after some manipulation, the equilibrium price of the stocks that are members of some index portfolios is given by

$$\xi_t S_{jt} = E_t[\xi_T D_{jT}]$$
$$= \xi_0 S_{MKT\ 0} E_t \left[\frac{D_{jT}}{D_T} \left[1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1 + b I_0^h} \left(I_t^h - I_0^h \right) \right] \right]. \tag{D.10}$$

Log-normal distributions give

$$E_t \left[\frac{D_{jT}}{D_T} \right] = e^{(\|\boldsymbol{\sigma}\|^2 - \boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma})(T-t)} \frac{D_{jt}}{D_t}$$

$$E_t \left[\frac{D_{jT} I_T^h}{D_T} \right] = e^{(\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h + \|\boldsymbol{\sigma}\|^2 - \boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma} - \boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma})(T-t)} \frac{D_{jt} I_t^h}{D_t}.$$

After some manipulation, (D.10) becomes

$$\xi_t S_{jt} = \xi_0 S_{MKT\ 0} e^{(\|\boldsymbol{\sigma}\|^2 - \boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma})(T-t)} \frac{D_{jt}}{D_t}$$
$$\times \left[1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1 + b I_0^h} \left(e^{(-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma} + \boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h)(T-t)} I_t^h - I_0^h \right) \right]. \tag{D.11}$$

Combining (D.7) and (D.11) gives the equilibrium price of the stocks that are members of some index portfolios in (C.12). The price in the benchmark economy without institutions is obtained by setting $b = 0$.

The equilibrium price of the stocks that are not members of any index portfolios can be obtained by setting $\boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h = 0$. ■

D.3 Proof of Proposition 2

The equilibrium market portfolio price can be expressed as $S_{MKT\ t} = \bar{S}_{MKT\ t} X_t / Z_t$. Applying Itô's lemma gives me $\boldsymbol{\sigma}_{MKT\ t} = \boldsymbol{\sigma} + \boldsymbol{\sigma}_{X_t} - \boldsymbol{\sigma}_{Z_t}$ where

$$\boldsymbol{\sigma}_{X_t} = \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} I_t^h \boldsymbol{\sigma}_h}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}\left(I_t^h - I_0^h\right)}$$

$$\boldsymbol{\sigma}_{Z_t} = \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h \boldsymbol{\sigma}_h}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}\left(e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h - I_0^h\right)}.$$

After some manipulation, I obtain the equilibrium market portfolio return volatility as in (C.14).

The equilibrium price of the stocks that are members of some index portfolios can be expressed as $S_{jt} = \bar{S}_{jt} X_{jt} / Z_{jt}$. Applying Itô's lemma gives $\boldsymbol{\sigma}_{jt} = \boldsymbol{\sigma}_j + \boldsymbol{\sigma}_{X_{jt}} - \boldsymbol{\sigma}_{Z_{jt}}$, where

$$\boldsymbol{\sigma}_{X_{jt}} = \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} e^{-(\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma} + \boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h)(T-t)} I_t^h \boldsymbol{\sigma}_h}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}\left(e^{-(\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma} + \boldsymbol{\sigma}_j^\intercal \boldsymbol{\sigma}_h)(T-t)} I_t^h - I_0^h\right)}$$

$$\boldsymbol{\sigma}_{Z_{jt}} = \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h \boldsymbol{\sigma}_h}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}\left(e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h - I_0^h\right)}.$$

After some manipulation, I obtain the equilibrium return volatility of the stocks that are members of some index portfolios as in (C.14). The return volatility of the stocks that are not members of any index portfolios can be obtained from $S_{kt} = \bar{S}_{kt}$. ■

D.4 Proof of Proposition 3

Applying Itô's lemma to both sides of (D.8) gives

$$\boldsymbol{\kappa}_t^\intercal d\boldsymbol{\omega}_t = \boldsymbol{\sigma} d\boldsymbol{\omega}_t - \frac{\sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h} e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h \boldsymbol{\sigma}_h \boldsymbol{\omega}_t}{1 + \sum_{h=1}^{H} \frac{\lambda^h b}{1+bI_0^h}\left(e^{-\boldsymbol{\sigma}_h^\intercal \boldsymbol{\sigma}(T-t)} I_t^h - I_0^h\right)}. \quad \text{(D.12)}$$

■

Appendix E Supplementary Results

E.1 Estimation Procedure

Equation 12 can be estimated by nonlinear least squares (NLS), and Equation 13 can be estimated by ordinary least squares (OLS). In estimating Equation 12, I introduce an algorithm, starting with initial guess values of α and β.

1. Given α and β, estimate λ by NLS.

2. Given λ, estimate α and β by OLS.

3. Stop if the objective function is minimized. If not, go to step 1 with updated α and β.

E.2 Estimation with Equal Weights

I estimate Equations 12 and 13 using my data set for the period 1980 Q2 to 2020 Q2 with equal weights. Following the recommendation in Hou et al. (2020), I exclude microcaps (i.e., drop stocks with firm size below the 20th percentile of NYSE breakpoints) in estimating the models.

Table A.I presents the estimated parameters. The results are almost identical as in Table 1. Most importantly, the estimated λ is positive, suggesting that institutional investors are cautious when trading assets in which they have a large ownership stake (see Equation 6).

E.3 Estimation with Alternative Specification

One could argue that investors concerned about their price impact would care more about their ownership relative to trading volume rather than the total shares outstanding. This idea is reasonable, so I incorporate this measure in the below equation. Specifically, Equation 12 can be written as

$$\mathbb{E}\big[r_{k,t+1}\big] = \left[\phi \cdot \mathbb{E}\big[f_{t+1}\big] + \theta \cdot \mathbb{E}\big[f_{t+1}\big] \cdot \frac{1}{\acute{v}_{k,t}} \sum_i A_{i,t} \cdot \left(w_{i,k,t} \cdot \big(1 - \lambda \cdot \acute{s}_{i,k,t}\big) + \psi_{i,t} \right) \right], \quad \text{(E.1)}$$

where $\acute{v}_{k,t-1}$ is the quarterly dollar trading volume (instead of market value), and $\acute{s}_{i,k,t-1}$ is investor i's ownership in asset k scaled by quarterly trading volume (instead of total shares outstanding).

I estimate Equation E.1, and the parameter of interest is λ. As before, my goal is not to estimate ϕ, θ, and $\mathbb{E}\big[f_{t+1}\big]$ separately. Instead, I set $\phi \cdot \mathbb{E}\big[f_{t+1}\big] = \alpha$ and $\theta \cdot \mathbb{E}\big[f_{t+1}\big] = \beta$ and estimate α, β, and λ. Table A.II presents the estimation results. The conclusion remains unchanged. Institutional investors are cautious when trading assets in which they have a high ownership stake relative to trading volume.

E.4 Idiosyncratic Volatility

Appendix Table A.III presents the relationship between idiosyncratic volatility and the model-implied exposure or NIO. The results are mixed. When using the log specification, the model-implied exposure is negatively related to idiosyncratic volatility. In contrast, NIO is strongly related to idiosyncratic volatility. A percentile rank increase of 50 for NIO is associated with an increase in idiosyncratic volatility of 40 basis points. This relationship is driven by active rather than passive funds.

E.5 High-beta Stocks

Appendix Table A.IV shows the relationship between market betas and the model-implied exposure or NIO with interactions with an indicator variable for high-beta stocks (those with above-median betas). All interaction terms are economically and statistically significant. The results are consistent with the idea that institutional investors increase the riskiness of their portfolios partly by tilting toward risky stocks.

E.6 Portfolios with Alternative Measures

In Panel A of Appendix Table A.V, I regress the total 13F institutional ownership on the natural logarithm of market capitalization each month and form 10 portfolios in the next month based on the residuals (Residual IOR). The portfolios' returns and market betas exhibit similar patterns as in Table 7, yet the economic magnitudes are smaller. Panel (a) of Appendix Figure A.III shows the performance of these portfolios around the global financial crisis in 2008. Note that the economic magnitude of the crash is smaller than that in Figure 3, and there is no apparent sign of reversals. Panel (b) of Appendix Figure A.III shows that the total 13F ownership of the top decile portfolio is somewhat constant during the global financial crisis.

In Panel B of Appendix Table A.V, I regress 1−HHI on the natural logarithm of market capitalization each month and form 10 portfolios in the next month based on the residuals (Residual 1−HHI). The portfolios' returns and market betas exhibit similar patterns as in Table 7, yet the economic magnitudes are smaller. Panel (b) of Appendix Figure A.III shows the performance of these portfolios around the global financial crisis in 2008. Note that the economic magnitude of the crash is smaller than that in Figure 3, and there is a less apparent sign of reversals. Panel (d) of Appendix Figure A.III shows that the total 13F ownership of the top decile portfolio is somewhat constant during the global financial crisis.

The portfolios formed by HHI exhibit stronger patterns than the portfolios formed using total 13F ownership, yet they are weaker than the portfolios sorted by Residual NIO. The stronger patterns plausibly arise because high Residual 1−HHI captures a dispersed ownership structure. However, the high Residual 1−HHI stocks include stocks with low 13F institutional ownership, which implies a lower price impact. The high Residual NIO stocks have high *and* dispersed institutional ownership structures.

Figure A.I. Equilibrium

The figure plots the equilibrium volatility, market beta, Sharpe ratio, and premium against the number of institutional owners (NIO). I calibrate the model as follows: There are $N = 50$ stocks, indexed by $j = 1, ..., 50$, and $H = 50$ benchmark index portfolios, indexed by $h = 1, ..., 50$. The first index includes the first stock, the second index includes the first and the second stocks, ..., and the last (50th) index includes all stocks. The parameter values are $\lambda = 0.3$, $b = 1$, $t = 1$, $T = 20$, and $I_0^h = 1$ for all h. In addition, $I_t^h = 1.25$ for all h and $\boldsymbol{\sigma}_j = 0.3\boldsymbol{i}_j$ for all j, where $\boldsymbol{i}_j$ is an N-dimensional unit vector with the j^{th} element equal to 1 and the remaining values equal to 0. Further, $\boldsymbol{\sigma}_h = 0.3\sum_{j=1}^{M_h} \boldsymbol{i}_j/\sqrt{M_h}$ for all h, where M_h is the number of stocks in the index h and $\boldsymbol{\sigma} = 0.3\sum_{j=1}^{N} \boldsymbol{i}_j\sqrt{N}$.

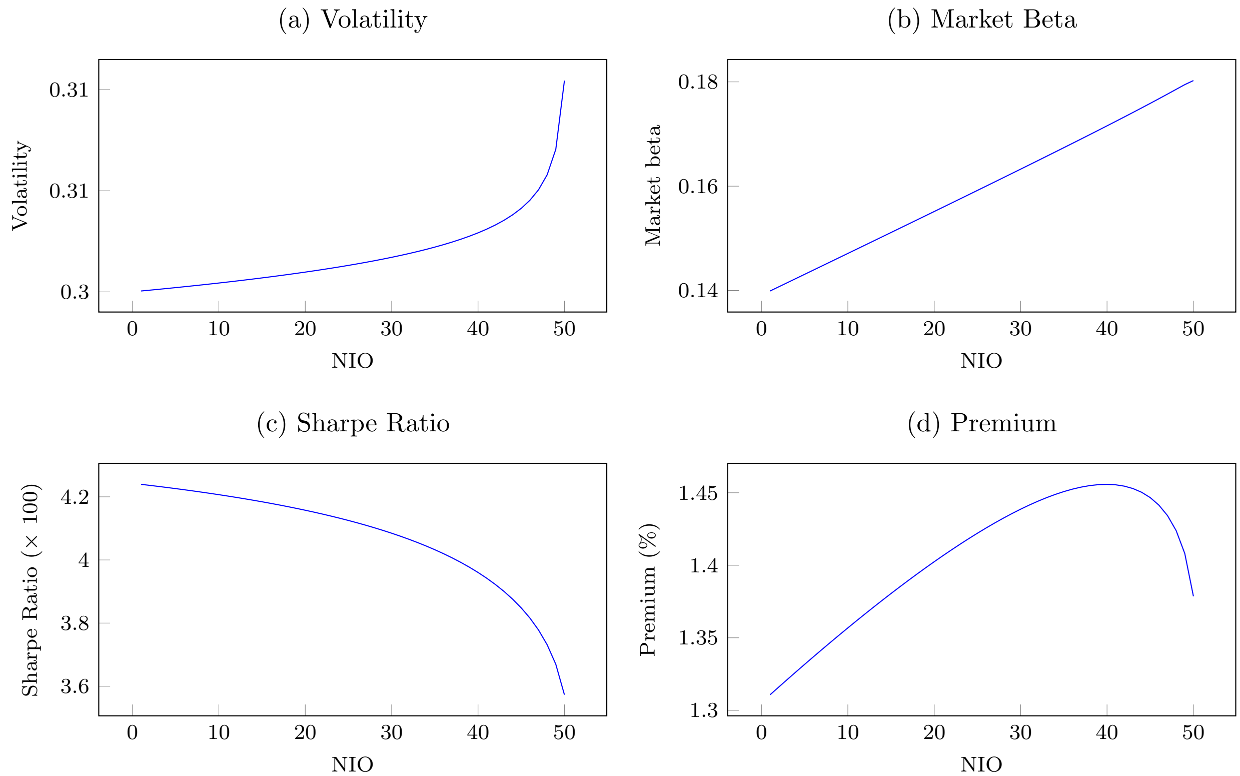


Figure A.II. Number of Funds Before Russell Reconstitution Events

The figure plots the number of active and passive owners in December (six months before the Russell reconstitution events) against May (one month before the reconstitution events) market capitalization rankings. The sample period spans the Russell reconstitution events between 2000 and 2006. Panel (a) shows the number of active funds, and Panel (b) reports the number of passive funds. Rank is stocks' market capitalization rankings in May. Rank equals −200 (200) if a stock is ranked 800th (1,200th). Each bin represents the average of 10 ranks over the sample period. The solid lines are the fitted lines using linear polynomials with a triangular kernel centered on the cutoff rank 0.

(a) Number of Active Funds

(b) Number of Passive Funds

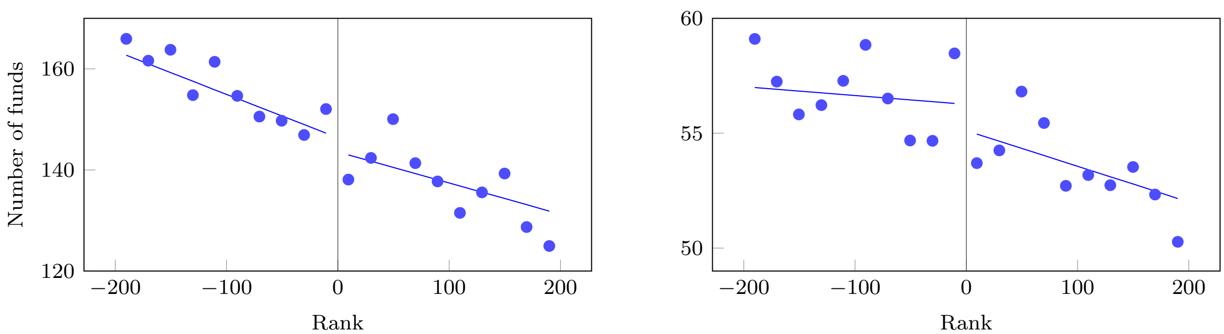
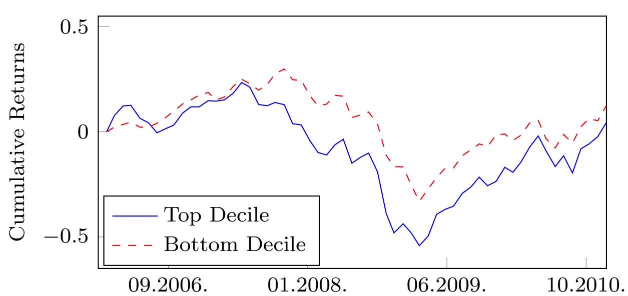


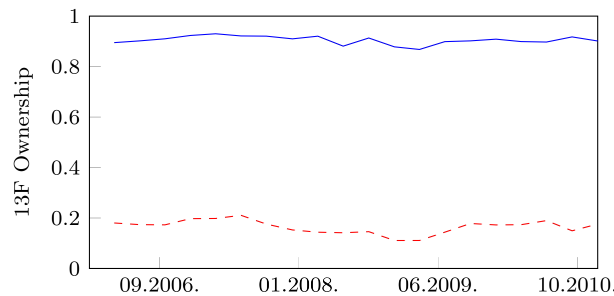
Figure A.III. Portfolio Returns and Institutional Ownership During the Global Financial Crisis

The figure shows the cumulative returns and the median 13F ownership of portfolios around the global financial crisis in 2008. The portfolios are formed as in Appendix Table A.V. I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership. In Panels (a) and (b), I regress total 13F institutional ownership on the natural logarithm of market capitalization each month and form 10 portfolios in the next month based on the residuals (Residual IOR). In Panels (c) and (d), I regress 1−HHI on the natural logarithm of market capitalization each month and form 10 portfolios in the next month based on the residuals (Residual 1−HHI). The portfolios are rebalanced monthly, and returns are value-weighted. Panels (a) and (c) present cumulative monthly returns of the top and the bottom decile portfolios, and Panels (b) and (d) report the median total 13F ownership of stocks in the top and the bottom decile portfolios.

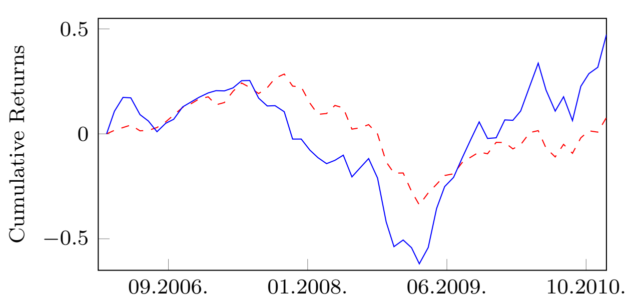
(a) Portfolio Returns
Portfolios Formed by Residual IOR



(b) Institutional Ownership
Portfolios Formed by Residual IOR



(c) Portfolio Returns
Portfolios Formed by Residual 1−HHI



(d) Institutional Ownership
Portfolios Formed by Residual 1−HHI

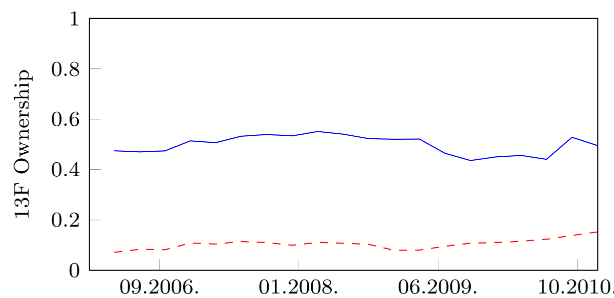


Table A.I. Estimation with Equal Weights

The table reports the parameter estimates from Equation 12 (Model I) and Equation 13 (Model II) with equal weights and the likelihood ratio test. Model I incorporates institutional investors' concern about the price impact of their trades, which is summarized by a parameter (λ) added to Model II. Model II is the benchmark model following the assumptions in Edmans et al. (2012). I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership and stocks with firm size below the 20th percentile of NYSE breakpoints. Standard errors are reported in brackets. The estimation procedures are detailed in Appendix E.

	Model I	Model II
α	0.028	0.027
	[0.009]	[0.009]
β	0.164	0.026
	[0.066]	[0.009]
λ	9.954	–
	[1.264]	–
Likelihood ratio	10.32	–
p-value	0.001	–

Table A.II. Estimation with Alternative Specification

The table reports the parameter estimates from Equation E.1 with equal weights (EW) and value weights (VW). I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership. I drop stocks with firm size below the 20th percentile of NYSE breakpoints for the estimation with equal weights. Standard errors are reported in brackets. The estimation procedures are detailed in Appendix E.

	EW	VW
α	0.027	0.025
	[0.008]	[0.006]
β	0.160	0.151
	[0.059]	[0.069]
λ	0.178	0.167
	[0.016]	[0.017]

Table A.III. Idiosyncratic Volatility

The table reports quarterly Fama and MacBeth (1973) regressions of idiosyncratic volatility on the number of institutional owners (NIO). I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership or negative book value from Compustat. Idiosyncratic volatility is the standard deviation of the residuals from the CAPM model using daily stock returns within each quarter (Sharpe, 1964; Lintner, 1965; Mossin, 1966). The independent variables are the log or the percentile rank of the number of 13F institutional owners (NIO), the number of active funds, and the number of passive funds. Mktcap is the quarter-end market capitalization, Price is the quarter-end stock price, and Book-to-market is book equity divided by market equity. Assets growth is the change in assets scaled by lagged assets (Fama and French, 2015; Hou et al., 2015), and Profitability is revenue minus the cost of goods sold scaled by total assets (Novy-Marx, 2013). Past-6-month return is the natural logarithm of cumulative past-6-month returns excluding the most recent month return, and the Amihud ratio is computed within each quarter following Amihud (2002). t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Idiosyncratic volatility$_{q+1}$					
Sample period:	1980-2020	1980-2020	1980-2020	1997-2020	1980-2020	1997-2020
log(Model-implied exposure$_q$)	−0.013***					
	(−2.66)					
log(NIO$_q$)		0.189***				
		(10.81)				
Rank: Model-implied exposure$_q$			0.000	0.002**		
			(0.70)	(2.45)		
Rank: NIO$_q$					0.008***	
					(11.70)	
Rank: NIO$_q$ (active)						0.009***
						(11.71)
Rank: NIO$_q$ (passive)						0.000
						(0.95)
log(Mktcap$_q$)	−0.175***	−0.315***	−0.195***	−0.224***	−0.300***	−0.324***
	(−23.07)	(−23.37)	(−21.57)	(−17.58)	(−24.17)	(−23.20)
1/Price$_q$	0.636***	0.620***	0.635***	0.941***	0.617***	0.921***
	(15.19)	(14.90)	(15.12)	(20.09)	(15.00)	(19.93)
log(Book-to-market$_q$)	−0.134***	−0.164***	−0.133***	−0.138***	−0.157***	−0.160***
	(−14.63)	(−17.56)	(−14.06)	(−10.32)	(−16.87)	(−12.25)
Assets growth$_{y-1}$	0.063***	0.080***	0.062***	0.045**	0.073***	0.054***
	(4.62)	(6.38)	(4.56)	(2.14)	(5.77)	(2.68)
Profitability$_{y-1}$	−0.147***	−0.206***	−0.158***	−0.173***	−0.206***	−0.239***
	(−7.06)	(−9.37)	(−7.51)	(−5.00)	(−9.37)	(−6.68)
Past 6-month return	−0.568***	−0.527***	−0.570***	−0.581***	−0.536***	−0.557***
	(−18.06)	(−17.34)	(−18.12)	(−12.16)	(−17.56)	(−11.99)
Amihud ratio$_q$	0.072***	0.092***	0.081***	0.113***	0.089***	0.120***
	(8.70)	(9.78)	(9.12)	(8.01)	(9.46)	(8.26)
Idiosyncratic volatility$_q$	0.521***	0.516***	0.522***	0.450***	0.518***	0.446***
	(42.06)	(42.12)	(42.43)	(31.24)	(42.15)	(31.69)
Observations	624,867	624,867	624,867	355,484	624,867	355,484
R-squared	0.546	0.547	0.545	0.484	0.547	0.486

Table A.IV. Amplification of Market Risk: High-beta Stocks

The table reports quarterly Fama and MacBeth (1973) regressions of market betas on the model-implied exposure (from Equation 12 in Section 3) and the number of 13F institutional owners (NIO) with interactions with an indicator variable for high-beta stocks. I include ordinary common shares (CRSP share codes 10 or 11) and stocks traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership or negative book value from Compustat. The market betas are computed by regressing daily stock returns in excess of the risk-free rates on contemporaneous and lagged value-weighted market returns in excess of the risk-free rates. The dependent variable is the sum of the two estimated coefficients. The main independent variables are the log or the percentile rank of the model-implied exposure, the number of 13F institutional owners (NIO), the number of active funds, and the number of passive funds. 1(High-beta) is an indicator variable that equals one if a stock has above-median beta. Mktcap is the quarter-end market capitalization, Price is the quarter-end stock price, and Book-to-market is book equity divided by market equity. Assets growth is the change in assets scaled by lagged assets (Fama and French, 2015; Hou et al., 2015), and Profitability is revenue minus the cost of goods sold scaled by total assets (Novy-Marx, 2013). Past-6-month return is the natural logarithm of cumulative past-6-month returns excluding the most recent month return, and the Amihud ratio is computed within each quarter following Amihud (2002). t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:		Beta_{q+1}		
Main variable: log(Model-implied exposure$_q$)	0.027***			
	(10.61)			
Main variable: log(NIO$_q$)		0.134***		
		(15.46)		
Main variable: Rank: Model-implied exposure$_q$			0.005***	
			(14.34)	
Main variable: Rank: NIO$_q$				0.006***
				(15.75)
Main variable × 1(High-beta)	0.013***	0.049***	0.003***	0.003***
	(27.84)	(27.19)	(26.56)	(25.93)
log(Mktcap$_q$)	−0.005	−0.061***	−0.048***	−0.059***
	(−0.91)	(−9.91)	(−8.83)	(−9.83)
1/Price$_q$	0.047***	0.027**	0.044***	0.029**
	(4.32)	(2.36)	(3.95)	(2.60)
log(Book-to-market$_q$)	−0.064***	−0.079***	−0.072***	−0.078***
	(−9.25)	(−10.87)	(−9.98)	(−10.82)
Assets growth$_{y-1}$	0.095***	0.106***	0.095***	0.101***
	(10.30)	(11.94)	(10.22)	(11.30)
Profitability$_{y-1}$	0.005	−0.017	−0.011	−0.018
	(0.41)	(−1.43)	(−0.90)	(−1.49)
Past 6-month return	−0.027	0.007	−0.028	0.003
	(−1.27)	(0.36)	(−1.32)	(0.16)
Amihud ratio$_q$	−0.050***	−0.047***	−0.056***	−0.053***
	(−7.44)	(−7.19)	(−7.53)	(−7.34)
Beta$_q$	0.173***	0.172***	0.184***	0.179***
	(16.42)	(16.95)	(17.33)	(17.24)
Observations	624,867	624,867	624,867	624,867
R-squared	0.177	0.183	0.180	0.184

Table A.V. Portfolios with Alternative Ownership Measures

The table reports the average value-weighted monthly returns and the CAPM alphas and betas of portfolios formed by 13F institutional ownership (IOR) or the Herfindahl-Hirschman index of 13F institutional ownership (HHI). I include ordinary common shares (CRSP share codes 10 or 11) traded on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, or 3). I exclude stocks with zero 13F institutional ownership. In Panel A, I regress total 13F institutional ownership on the natural logarithm of market capitalization each month and form 10 portfolios in the next month based on the residuals (Residual IOR). The portfolios are rebalanced monthly. In Panel B, I regress 1−HHI on the natural logarithm of market capitalization each month and form 10 portfolios in the next month based on the residuals (Residual 1−HHI). The portfolios are rebalanced monthly. Return is the time-series average of the value-weighted monthly portfolio returns. CAPM alphas and betas are estimated using the CAPM model (Sharpe, 1964; Lintner, 1965; Mossin, 1966). Returns and alphas are shown in percentages. t-statistics are adjusted for heteroscedasticity and autocorrelations.

Panel A: Portfolios Sorted by Residual IOR

Deciles	L	2	3	4	5	6	7	8	9	H	H−L
Return	0.94	1.03	1.04	1.11	1.16	1.11	1.10	1.20	1.09	1.09	0.15
t(Return)	4.44	4.67	4.63	4.97	5.16	4.98	5.08	5.09	4.66	4.34	0.84
CAPM α	−0.03	0.02	0.04	0.05	0.11	0.00	0.00	0.06	−0.07	−0.11	−0.08
t(CAPM α)	−0.44	0.38	0.67	0.87	1.39	0.04	0.01	0.52	−0.61	−0.77	−0.41
CAPM β	0.91	0.97	0.95	1.03	1.03	1.10	1.10	1.16	1.19	1.24	0.33

Panel B: Portfolios Sorted by Residual 1−HHI

Deciles	L	2	3	4	5	6	7	8	9	H	H−L
Return	0.91	1.00	1.12	1.07	1.12	1.16	1.19	1.22	1.22	1.42	0.50
t(Return)	4.14	4.69	5.22	4.91	4.98	4.92	4.76	4.64	4.31	4.25	1.73
CAPM α	−0.06	−0.01	0.05	−0.04	−0.01	−0.01	0.01	0.02	0.01	0.15	0.21
t(CAPM α)	−0.61	−0.24	0.82	−0.49	−0.13	−0.05	0.10	0.14	0.04	0.65	0.75
CAPM β	0.92	0.97	1.05	1.11	1.14	1.20	1.21	1.24	1.26	1.34	0.43