# A Bound on Price Impact and Disagreement*

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**Abstract**

High asset price volatility alongside low portfolio flows reveals a fundamental trade-off between investor disagreement and price impact: When volatility is high but flows are small, investors must either largely agree with each other or be insensitive to price changes, implying large price impacts of small flows. We formalize this relationship in a price impact bound based on price volatility, flow volatility, and investor agreement. Applying our bound to U.S. equities yields large price impacts, implying that flows are central to understanding price dynamics. Our bounds align with event-study estimates while revealing novel patterns across horizons, assets, and aggregation levels.

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# 1 Introduction

It is uncontroversial that investors often disagree with each other. Such disagreement gives rise to heterogeneous portfolio holdings and flows. However, how much flows matter for asset prices is still an active debate, reflecting two different views on asset pricing. In one view, investors are highly elastic with respect to asset prices, and hence the market clears trading with little price adjustment. Under this view, quantity data – portfolio holdings and flows – tells us little about the drivers of asset prices. By contrast, in the inelastic market view, quantities have a significant impact on prices, making portfolio holdings and flows central to understanding asset prices.

In this paper, we argue that, given observable moments on quantities and prices, if we acknowledge that investors disagree with each other, we must accept the inelastic market view – that trading has a large price impact. Our argument rests on a simple observation: asset prices are highly volatile, yet portfolio flows – changes in portfolio holdings – are relatively small. This observation creates a trade-off between *investor agreement* and *price impact*: with large agreement among investors, one can easily generate little (or no) trading alongside volatile prices. However, with large disagreement, one might expect to observe large trading among investors. Yet we do not, despite high price volatility. Hence, this observation must imply that investors are insensitive to price changes, i.e., price-inelastic. As a result, small portfolio flows have large price impacts. This fundamental tension between price impact and agreement forms the core insight of our paper.

We formalize the trade-off between price impact and agreement mathematically as a simple bound based on two directly observable moments: portfolio flow volatility $\sigma_q$ and return volatility $\sigma_p$. We define *investor agreement* $\rho$, loosely speaking, as the correlation of demand shifts across investors.[1] Within our framework, *demand shifts* are defined as any change in investors' portfolio choice, holding prices constant (e.g., cash flow news). Demand shifts can diverge for many reasons beyond disagreement about cash-flow news – for example, disagreement about discount rates, changes in regulatory frictions, etc. Importantly, what matters is the agreement in demand *shifts*, as opposed to agreement in *levels*. Investors may strongly disagree about the level of prices, yet still largely agree on how new information changes prices. *Price impact* $\mathcal{M}$ is given by the percentage change in prices per 1% demand shift.

Our main theoretical result establishes that the price impact $\mathcal{M}$ is bounded from below as follows:

$$\mathcal{M} \geq \frac{\sigma_p}{\sigma_q} \times \sqrt{\frac{1}{\rho} - 1}. \tag{1}$$

[1] Formally, $\rho$ is defined as the share of demand shift variation explained by the size-weighted cross-investor average.

The bound captures our key insight: high return volatility $\sigma_p$ relative to portfolio flow volatility $\sigma_q$ (i.e., a high p/q volatility ratio) implies either high price impact (high $\mathcal{M}$) or high agreement among investors (high $\rho$). To understand the intuition, consider the analogy of total demand shifts as an iceberg: only disagreement surfaces as observable portfolio flows, while common demand shifts remain submerged. Investor agreement $\rho$ determines the relative size of observable versus unobserved demand shifts. When investors perfectly agree ($\rho \to 1$), observed flows represent only the tip of the iceberg, while the price is moved by large unobserved common demand shifts, making the p/q ratio uninformative about price impact. Conversely, when investors disagree (small $\rho$), visible flows represent most total demand shifts with only small common demand shifts beneath the surface, so large return volatility requires substantial price impact.

These two scenarios, while both consistent with observed flow and return volatilities, have fundamentally different implications for our understanding of asset prices. In the case of elastic investors that largely agree with each other, portfolio holdings and flows are merely a sideshow – they capture at best minor deviations from common demand shifts which drive prices. In such a world, asset prices can be well-described by representative agent models, while portfolio flows across investors are a largely irrelevant byproduct of price formation. In contrast, in the case of inelastic investors that disagree with each other, portfolio flows carry substantial incremental information about asset prices. Here, observed quantities are no longer irrelevant but central to our understanding of asset prices.

The derivation of our bound relies on a set of fairly general assumptions. Most notably, following the long tradition of log-linearization in finance and the growing literature on demand-system asset pricing (Campbell and Viceira, 2002; Koijen and Yogo, 2019), we assume that portfolio choice problems can be approximated to a first order by linear demand curves. Importantly, we impose no structural assumptions on the source or structure of demand shifts, nor on particular microfoundations of the elasticities. This makes our bound *empirical* in nature, similar in spirit to the Hansen–Jagannathan bound (Hansen and Jagannathan, 1991). Due to the model-agnostic nature of the bound, it can serve as a diagnostic tool when developing structural models to rationalize these moments. It can also be used in empirical studies when estimating price impact $\mathcal{M}$ or agreement $\rho$ to back out the other parameter, thus providing a more comprehensive picture of the market environment.

We apply our bound in Equation (1) to the US stock market. Returns are volatile: an average stock has a return volatility of $\sigma_p \approx 20\%$ at the quarterly frequency. On the other hand, flow volatility is not much larger. We show that flow volatility $\sigma_q$ can be simply measured with "portfolio turnover", the net portfolio reallocations across all investors over the period of interest. At the quarterly frequency, the average stock has a portfolio turnover of around 20%, resulting in a p/q volatility ratio of $\frac{\sigma_p}{\sigma_q} \approx 1$. A high $p/q$ volatility ratio is not an artifact of our specific measure. When we proxy flows using total trading volume at the daily frequency, we obtain a ratio of comparable magnitude, and in fact somewhat higher in the earlier sample period.

Flow and return volatilities are readily measurable in the data, but investor agreement $\rho$, the correlation of investors' demand shifts, is inherently unobservable. However, there is substantial empirical evidence confirming that investors' demand shifts are far from perfectly correlated ($\rho \ll 1$). Investors differ markedly in their cash-flow forecasts, regulatory constraints, return expectations, trading patterns, and portfolio compositions.[2] Given this evidence, a highly elastic market at the quarterly frequency appears unlikely through the lens of our bound. For example, as $\frac{\sigma_p}{\sigma_q} \approx 1$ for the average stock, achieving a price impact below 0.1 requires almost perfect agreement among investors, i.e., $\rho > 0.99$.

To estimate the price impact bound, we incorporate empirical proxies for investor agreement $\rho$. Our goal is not to obtain precise point estimates, but to demonstrate that $\rho$ lies within a moderate range – avoiding pathological extremes near zero or one. Our baseline proxy measures agreement through the common variations in earnings forecast updates across analysts. For the average U.S. firm, forecast updates of earnings per share (EPS) across analysts explain approximately 57% of the total variation in EPS forecast updates, yielding $\rho = 0.57$. When we use long-term growth (LTG) forecasts instead, we obtain $\rho = 0.32$. Applying these agreement measures to our model generates stock-level price impacts of 0.75 and 1.25, respectively. We also draw on proxies for $\rho$ from event studies and structurally inferred demand shifts, and find no evidence that $\rho$ takes implausibly high values.

The model parameter $\rho$ should reflect all forms of heterogeneity in demand shifts, including belief disagreement, regulatory constraints, and preferences, which may not be fully reflected in our empirical proxies for $\rho$. However, our measures suggest that the true value of $\rho$ lies in the moderate range rather than at the extremes. In the moderate range, $\sqrt{\frac{1}{\rho} - 1}$ is relatively flat, making it insensitive to variations in $\rho$. Consequently, cross-stock variation in our bounds is driven primarily by the p/q volatility ratio, $\frac{\sigma_p}{\sigma_q}$. In fact, an approximated price impact estimate $\tilde{\mathcal{M}} \equiv \frac{\sigma_p}{\sigma_q}$ (which implicitly assumes $\rho = 0.5$) performs nearly as well empirically as the general bound.

We empirically validate our price impact bounds against well-documented demand shock events,

[2]See, among others, Giglio et al. (2021), Koijen and Yogo (2019), Dahlquist and Ibert (2024), Couts et al. (2024), Barber and Odean (2008), Guiso, Sapienza, and Zingales (2008), Kandel and Pearson (1995). In addition, the vast investor disagreement can be directly observed by the fact that the number of different mutual funds catering to the preferences and beliefs of different investors exceeds the number of stocks in the U.S. (see Investment Company Institute (2025)).

including S&P 500 index inclusions and mutual fund flow-induced trading. Our bound-implied price impact estimates exhibit strong correlations with actual price movements across these events. Stocks with larger bounds experience significantly higher price changes for a given demand shock. For instance, the price impact of flow-induced trades increases monotonically with our bounds. In contrast, traditional liquidity measures based on gross trading volume, such as Amihud's (2002) illiquidity ratio, show no significant explanatory power for price impacts estimates.

Assuming $\rho$ lies in a moderate range, our approximated price impact measure $\tilde{\mathcal{M}}$ enables us to explore heterogeneity in price impacts across settings where event study evidence is scarce. We examine how the price impact bounds vary at different horizons, across assets, and at different levels of aggregation. First, price impact declines monotonically with horizon – that is, demand elasticities increase at longer horizons. Daily price impacts are substantially larger than quarterly impacts, which in turn exceed annual impacts. Second, while daily price impact has declined significantly from 1990 to 2024, quarterly and annual price impacts have remained largely unchanged. Third, we find systematic patterns in the cross-section: large-cap stocks exhibit *smaller* price impact, consistent with the notion that large-caps are more liquid, while stocks with higher systematic risk show *larger* price impact, consistent with risk-based foundations. Momentum stocks also experience higher price impact, reflecting upward-sloping demand curves of momentum investors. Fourth, examining our bounds at different levels of aggregation reveals that portfolio turnover falls quickly as aggregation increases, since portfolio flows in similar assets offset each other – for example, trading Apple against Microsoft creates stock-level turnover but none at the tech-sector level. While return volatility also declines due to diversification, turnover decreases faster, implying that our price impact bounds rise monotonically with aggregation – from individual stocks, to industries, to size/value portfolios, and ultimately to the aggregate market (Gabaix and Koijen, 2021).

Our bounds provide a measure of how informative portfolio flow data is for asset prices. When demand is highly elastic, portfolio flows reveal little about prices as demand shifts can be easily accommodated with minimal price impact. Conversely, when demand is inelastic, portfolio flows are highly informative for prices. Empirically, our bounds suggest that the stock market is closer to the "inelastic and heterogeneous" paradigm than to the "elastic and homogeneous" paradigm. In such markets, observed portfolio flows reveal a significant portion of the underlying demand variation, and have significant impact on prices. Echoing Hong and Stein (2007) and more recently Gabaix and Koijen (2021), our bounds demonstrate that trading volume is not a mere byproduct of price formation, but is essential for understanding asset prices and financial market volatility.

**Related Literature.** Following the work by Koijen and Yogo (2019) and Gabaix and Koijen (2021), a fast growing literature jointly models data on asset prices and investor demand, such as portfolio holdings and flows. These structural models enable us to answer a broad set of questions related to the role of holdings and flows and investor heterogeneity in asset markets (Jiang, Richmond, and Zhang, 2024; Koijen, Richmond, and Yogo, 2024; Haddad, Huebner, and Loualiche, 2025; Koijen, Shah, and Van Nieuwerburgh, 2025; see Haddad and Muir, 2025 for a comprehensive review).[3] However, identification of price elasticities, the key parameter in these models, poses an empirical challenge. The existing literature typically relies on exogenous variation in investor demand, either through model-based instruments (Gabaix and Koijen, 2024) or plausibly exogenous demand shifts such as investment mandates (Koijen, Richmond, and Yogo, 2024), dividend reinvestments (Hartzmark and Solomon, 2025), and index rebalancing (Pavlova and Sikorskaya, 2023).[4] Conceptually, we highlight that these instruments generate effective disagreement across investors, which enables the identification of demand elasticities from conditional moments. Methodologically, our bound provides a complementary approach to understanding price elasticities in asset markets. We use two simple unconditional moments—portfolio turnover and return volatility—without relying on exogenous instruments. The price impact implied by our bound closely aligns with the magnitudes found in these studies, and further offers a theoretically grounded benchmark for settings where event studies are scarce or infeasible.

The literature has recognized the tension between price elasticity and investor heterogeneity. Gabaix and Koijen (2021) argue that the relatively stable equity share of institutional investors implies inelastic demand at the aggregate market level. Their granular instrumental variable (GIV) estimator imposes a factor structure on demand shifts and measures investor agreement by extracting common components from investor flows. Chaudhary, Fu, and Zhou (2024) further develop an optimal GIV estimator, in which the potential bias in elasticity estimates is tied to the $R^2$ of hidden comovement in investor demand shifts, reflecting the same elasticity-heterogeneity trade-off emphasized in this paper. Gabaix, Koijen, et al. (2025) compute "risk transfers" as changes in households' aggregate market exposure, which is conceptually close to portfolio turnover. They demonstrate that standard macro-

[3]Other applications include Han, Roussanov, and Ruan (2021), Chaudhry (2022), Coqueret (2022), Darmouni, Siani, and Xiao (2022), Fang, Hardy, and Lewis (2022), Jiang, Richmond, and Zhang (2022), Chaudhary, Fu, and Li (2023), Huebner (2023), Chaudhary, Fu, and Zhou (2024), Jansen, Li, and Schmid (2024), Koijen, Richmond, and Yogo (2024), Tamoni, Sokolinski, and Li (2024), Bretscher, Schmid, Sen, et al. (2025), Chaudhry and Li (2025), and Jansen (2025)

[4]Other evidence includes Greenwood (2005), Coval and Stafford (2007), Lou (2012), Chang, Hong, and Liskovich (2015), Kvamvold and Lindset (2018), Ben-David et al. (2022), Li and Lin (2022), Schmickler and Tremacoldi-Rossi (2022), Greenwood, Laarits, and Wurgler (2023), Cassella et al. (2024), Bretscher, Schmid, and Ye (2025), Greenwood and Sammon (2025), and Honkanen, Zhang, and Zhou (2025).

finance models with high price elasticities cannot reconcile the limited risk transfer with large observed heterogeneity in holdings. Our paper formalizes and generalizes this tension in a *model-free* statistical bound that does not rely on a specific structural model linking heterogeneous portfolios to unobserved demand shifts.

Our bounds also connect to the literature on trading volume and investor disagreement. Kandel and Pearson (1995) and Bamber, Barron, and Stober (1999) document that earnings announcement days consistently feature abnormally high trading volume combined with small price changes. This combination of high volume and low volatility is typically interpreted as evidence of differential interpretations of public signals, i.e., *disagreement*. Hong and Stein (2007) advocate for models featuring disagreement, given the high trading volume observed even when return volatility is low.[5] Importantly, while we find that portfolio turnover is low at longer horizons, we argue that this does not reflect an absence of disagreement. Instead, low turnover combined with high return volatility reflects the inelasticity of market participants: even modest investor-specific demand shifts generate large price movements. This interpretation is consistent with substantial heterogeneity in subjective return expectations documented among both households and asset managers (e.g., Dahlquist and Ibert, 2024), and aligns with a large literature emphasizing the role of subjective beliefs in asset pricing.[6]

The remainder of the paper is structured as follows. Section 2 lays out the main theory. Section 3 describes the data, construction of portfolio turnover, and its empirical properties. Section 4 constructs the price impact bounds for the cross-section of U.S. equities; Section 5 tests the empirical relevance of the bounds using different event studies. Motivated by the empirical relevance, Section 6 then examines the heterogeneity of these bounds outside of event studies – over time, across assets, and at different levels of aggregation. Section 7 concludes.

## 2 Theory

In this section, we lay out our main framework and derive the price impact bound.

**Notation.** Throughout, we use $i = 1, 2, ..., I$ to denote the investor, $n$ to denote the asset. We use $S_i(n)$ to denote the ownership share of investor $i$ in the market for asset $n$. As a short-hand, we use subscript $S$ in place of $i$ to denote size-weighted aggregation, i.e., $x_S(n) = \sum_{i=1}^{I} S_i(n) x_i(n)$.

[5] See, for example, Harris and Raviv (1993) and Banerjee and Kremer (2010) for theoretical models reconciling the observed empirical patterns.

[6] See Greenwood and Shleifer (2014), Malmendier and Nagel (2016), Bordalo et al. (2020), Delao and Myers (2021), Giglio et al. (2021), Nagel and Xu (2022), Adam and Nagel (2023), and Delao and Myers (2024) for an incomplete list of studies examining heterogeneity in expectation formation among economic agents.

To highlight the cross-sectional expectation-like feature of the size-weighted aggregation, we also use $\hat{\mathbb{E}}_S^{cs}[x_i(n)] = \sum_{i=1}^{I} S_i(n)x_i(n)$, and suppress the subscript $S$ when there is no ambiguity.

## 2.1 The Demand Curve

For illustration purposes, we start by deriving the price impact bound in a single-asset portfolio-choice model. We suppress $n$ for notational simplicity. Then we show in Section 2.6 that our bound applies to a multi-asset setting as well.

Consider a generic portfolio allocation $Q_{i,t} = \mathcal{Q}_i(P_t, U_{i,t})$, where $Q_{i,t}$ is the quantity held by investor $i$ at time $t$, $P_t$ is the asset price at time $t$, and $U_{i,t}$ captures all other factors that affect investor $i$'s demand at the given price $P_t$. These factors can include the investor's wealth, the risk-free rate, risk aversion, uncertainty, prices of substitutable assets, and other relevant variables.

We take a log-linear approximation of the portfolio choice problem around the long-run mean and take first-differences to obtain a linear demand curve:

$$\Delta q_{i,t} = -\zeta_i \Delta p_t + u_{i,t} \tag{2}$$

where $\Delta q_{i,t}$ is the percentage change in holdings by investor $i$ at time $t$ (which we refer to as *portfolio flows* or simply *flows*), $\Delta p_t$ is the percentage price change at time $t$, referred to as the return at time $t$, and $u_{i,t}$ is the demand shift for investor $i$ at time $t$. For simplicity, we assume that their time-series means are equal to zero. The parameter $\zeta_i$ is the investor-specific elasticity, which measures how much investor $i$'s demand changes when the price changes by 1%, *ceteris paribus*.

To provide intuition for the different components of the demand curve, we can connect this linear specification with canonical models. In Appendix B, we sketch several microfoundations, including standard portfolio choice under CRRA utility. Our preferred interpretation draws on learning-from-price models such as Grossman and Stiglitz (1980) and Hellwig (1980). In these models, the demand shift $u_{i,t}$ represents noisy private signals about the asset's fundamental value, while the price $P_t$ aggregates information across investors. The price elasticity $\zeta_i$ captures the trade-off between the informativeness of one's private signal and the market price: the more accurate the market price is relative to the investor's private signal, the more the investor relies on the price, resulting in a more inelastic demand curve (smaller $\zeta_i$).

While learning-from-price models provide a natural framework for interpreting elasticity and disagreement, we do not restrict our analysis to this interpretation. Instead, we specify the demand curve generically. In any asset pricing model that features portfolio choice, either explicitly or implicitly, investor demand can be decomposed into changes due to price movements and changes holding prices fixed.[7] Our bound holds under these different model frameworks. Moreover, the underlying model does not need to be static: in dynamic settings, investors care about the path of future expected returns, while the market clears through the current price, which summarizes the market's expectations about future returns. In this case, investors' demand shifts contain beliefs about future expected returns that deviate from those implied by the current price. Furthermore, our framework also readily accommodates multiple assets – as shown in Section 2.6, a multi-asset system also yields a single-asset demand representation as in (2). Our only assumption at this stage is that a first-order log-linearization provides a reasonable approximation of the true portfolio choice problem.

For a generic demand curve specified in Equation (2), our goal is to connect elasticity and the correlation of demand shifts (agreement) to observable moments: volatilities of returns and portfolio flows. To do so, we first study how the return and flow volatilities are determined in the log-linear model.

## 2.2 Elasticity and Price Impact

The flip side of elasticity is the price impact per unit of demand shift. To see that, we impose the market clearing condition – all trades sum to zero. Denote $S_i = \frac{\bar{Q}_i}{\sum_i \bar{Q}_i}$ the ownership share of investor $i$ in the market. The market clearing condition is given by:

$$\sum_i S_i \Delta q_{i,t} = 0 \tag{3}$$

Price adjusts to clear the market, and hence,

$$\Delta p_t = \frac{1}{\zeta_S} u_{S,t} \tag{4}$$

where $\zeta_S = \sum_i S_i \zeta_i$ and $u_{S,t} = \sum_i S_i u_{i,t}$ are the aggregate elasticity and demand shift given by the size-weighted averages of investor-specific elasticities and investor-specific demand shifts respectively. The inverse of the aggregate elasticity, $\frac{1}{\zeta_S}$, quantifies how much the price adjusts when aggregate demand shifts by 1% of total outstanding shares. Therefore, the lower the aggregate demand elasticity, the larger is the price adjustment per unit of demand shift which is needed to induce investors to step

[7]See Koijen and Yogo (2025) for further discussion on microfoundations.

in. We denote the inverse of the aggregate demand elasticity as $\mathcal{M}$ and refer to it as the *price impact* or *multiplier*. Formally,

$$\mathcal{M} \equiv \frac{1}{\zeta_S}. \tag{5}$$

The price impact $\mathcal{M}$ links return volatility to the volatility of the aggregate demand shift, given by:

$$\sigma_p^2 = \mathcal{M}^2 \cdot \mathrm{Var}(u_{S,t}) \tag{6}$$

Through the lens of this framework, the well-known excess volatility puzzle implies that either standard models do not generate sufficiently volatile aggregate demand shifts, or that agents are too responsive to price changes in these models, i.e., the price impact $\mathcal{M}$ is too small.

## 2.3 Portfolio Flows and Investor Agreement

To illustrate the relationship between portfolio flows and investor agreement, we first consider the case with homogeneous elasticities across investors: $\zeta_i = \zeta_S = \zeta$. This assumption will be relaxed later. Under the homogeneous elasticity assumption, we can plug the equilibrium price equation (4) into the demand equation (2) to have:

$$\Delta q_{i,t} = u_{i,t} - u_{S,t}. \tag{7}$$

Hence, trades reflect the *differences* of investors' demand shifts from the average demand shift in the market.

The size-weighted average variance of $\Delta q_{i,t}$ is given by:

$$\begin{aligned} \sigma_q^2 &\equiv \sum_{i=1}^{I} S_i \,\mathrm{Var}\left(\Delta q_{i,t}\right) \\ &= \left(\sum_{i=1}^{I} S_i \,\mathrm{Var}(u_{i,t})\right) - \mathrm{Var}\left(u_{S,t}\right) \end{aligned} \tag{8}$$

To derive the second equality, we use Equation (7) and the identity $\sum_{i=1}^{I} S_i \,\mathrm{Cov}(u_{i,t}, u_{S,t}) = \mathrm{Var}(u_{S,t})$. Hereafter, we refer to $\sigma_q$ as *flow volatility*. It measures the total amount of trading activity by investors. The theoretical analysis focuses on flow volatility defined in (8); later we show that portfolio turnover across all investors is a close proxy for flow volatility, and use the terminology interchangeably when the distinction is unimportant.

Defining $\rho \equiv \frac{\text{Var}(\sum_{i=1}^{I} S_i u_{i,t})}{\sum_{i=1}^{I} S_i \text{Var}(u_{i,t})}$, we can rewrite flow volatility as follows:

$$\sigma_q^2 = \text{Var}(u_{S,t}) \left( \frac{1}{\rho} - 1 \right). \tag{9}$$

We refer to $\rho$ as *investor agreement.* To understand the interpretation, note that it is the share of demand shifts that is explained by the size-weighted cross-sectional average of the demand shifts. To see this most clearly, we can use the cross-sectional expectation notation $\hat{\mathbb{E}}^{cs}$ to express it as follows:

$$\rho = \frac{\text{Var}\left( \hat{\mathbb{E}}^{cs} \left[ u_{i,t} \mid t \right] \right)}{\hat{\mathbb{E}}^{cs} \left[ \text{Var} \left( u_{i,t} \mid i \right) \right]} \in [0, 1]. \tag{10}$$

Empirically, $\rho$ is the $R^2$ of the (size-weighted) time fixed effects of the demand shifts. As an $R^2$, it ranges between 0 and 1. When $\rho = 1$, all investors have identical demand shifts, and hence are homogeneous; when $\rho \to 0$, the demand shifts are completely heterogeneous across investors.[8] Alternatively, with homoskedasticity, the agreement $\rho$ can be loosely interpreted as the average pairwise correlation of the demand shifts $\rho \approx \sum_{i=1}^{I} \sum_{j \neq i} S_i S_j \ \text{corr}(u_{i,t}, u_{j,t})$.[9]

Note that disagreement comes not only from differences in idiosyncratic demand shifts, but also from differences in the responses of different investors to common factors. To see this, suppose investor-specific demand shifts are determined by their differential exposure $\lambda_i$ to a single common shock $\eta_t$, which has unitary variance, i.e., $u_{i,t} = \lambda_i \eta_t$. Let $\hat{\mathbb{E}}^{cs}$ denote the size-weighted cross-sectional average, we have $\rho = \frac{\hat{\mathbb{E}}^{cs}[\lambda_i]^2}{\hat{\mathbb{E}}^{cs}\left[\lambda_i^2\right]} = \left( 1 + \frac{\widehat{\text{Var}}^{cs}(\lambda_i)}{\hat{\mathbb{E}}^{cs}[\lambda_i]^2} \right)^{-1}$. It implies that investor agreement decreases in the dispersion of loadings on the common shock $\eta_t$ across investors. Further, agreement can be arbitrarily close to zero when the variation in $\lambda_i$ relative to its mean is large. In sum, investors can have low agreement even if their demand shifts can be fully explained by a common shock, $\eta_t$, provided their exposures to that shock differ.

With this interpretation, the factor $\frac{1}{\rho} - 1$ in Equation (9) has an intuition interpretation: it is the ratio of the disagreement, reflected in the observed flows $\sigma_q^2$, to the common demand shifts $Var(u_{S,t})$.

[8]With finite number of investors, $\rho \geq \frac{\sum_i S_i^2 \sigma_i^2}{\sum_i S_i \sigma_i^2}$ if the covariances of the demand shifts across investors are non-negative, and it reaches the lower bound when shocks are completely uncorrelated. It reaches zero only if investors demand completely offset each other in aggregate.

[9]We can write $\text{Var}(u_{S,t}) = \sum_{i=1}^{I} S_i^2 \sigma_i^2 + \sum_{i=1}^{I} \sum_{j \neq i} S_i S_j \sigma_i \sigma_j \ \text{corr}(u_{i,t}, u_{j,t})$, under homoskedasticity, $\sigma_i = \sigma_j = \sigma$, so we have $\rho = \sum_{i=1}^{I} S_i^2 + \sum_{i=1}^{I} \sum_{j \neq i} S_i S_j \ \text{corr}(u_{i,t}, u_{j,t})$. The first term is the Herfindahl–Hirschman Index (HHI) of the ownership distribution, which vanishes to zero as $N$ is large.

Rearranging Equation (9) makes this explicit:

$$\frac{\sigma_q^2}{\text{Var}(u_{S,t})} = \frac{1-\rho}{\rho}. \tag{11}$$

## 2.4 The Price Impact Bounds

To derive the bound, the key observation is that both price volatility (6) and flow volatility (9) depend on the volatility of the average demand shift in the market, but with different coefficients: the multiplier $\mathcal{M}$ for return volatility and the factor $\frac{1}{\rho} - 1$ for flow volatility. Taking the ratio of flow volatility in Equation (9) and return volatility in Equation (6), we have:

$$\mathcal{M} = \frac{\sigma_p}{\sigma_q} \times \sqrt{\frac{1}{\rho} - 1} \tag{12}$$

Equation (12) connects observable market quantities – price and flow volatilities – to the underlying elasticity and investor agreement. When prices exhibit high volatility relative to trading activity (a large $\frac{\sigma_p}{\sigma_q}$ ratio), two possible explanations emerge: either the price multiplier $\mathcal{M}$ is large, amplifying price responses to demand shifts, or investors strongly agree with each other on demand shifts ($\rho \to 1$), causing observed trading activity (the tip of the iceberg of total demand shifts) to significantly underrepresent the magnitude of underlying demand shifts.

So far, we have derived price impact $\mathcal{M}$ under the homogeneous-elasticity assumption. To allow for heterogeneous elasticities, we need to account for their cross-sectional distribution. Without committing to a particular microfoundation, we consider the following benchmark in which the parameters governing elasticities are independent of those governing demand shifts:

**Assumption 1.** *In the cross section, the elasticity $\zeta_i$ for each investor $i$ is independent of the data-generating process for the demand shift $u_{i,t}$.*

We adopt this assumption because it offers a transparent and tractable benchmark, though it is not required for our main theorem. Appendix A shows that the bound also holds under a weaker (but more technical) condition on the joint distribution of elasticities and demand shifts.

Under Assumption 1, heterogeneity in elasticities acts like a mean-preserving spread: it leaves aggregate price responses unchanged while amplifying individual trading activity. Price volatility remains $\sigma_p^2 = \mathcal{M}^2 \,\text{Var}(u_{S,t})$, but flow volatility $\sigma_q$ increases because heterogeneous elasticities create additional trading motives beyond disagreement in demand shifts. Even when two investors receive identical demand shifts, they respond differently to the resulting price change: the more elastic investor trades more aggressively, generating additional flow. Consequently, an econometrician who infers aggregate demand shifts from observed flow volatility while assuming homogeneous elasticities will overestimate the true magnitude of demand shifts. This overestimation occurs because some observed trading activity stems not from disagreement in demand shifts but from investors' heterogeneous responses to price changes. Since the true aggregate demand shifts are smaller than the value inferred by the econometrician, the actual price impact exceeds that given by (12). Formally, we establish the following theorem:

**Theorem 1.** *Under Assumption 1, the price impact* $\mathcal{M}$ *of demand shifts is lower-bounded by the p/q volatility ratio* $\frac{\sigma_p}{\sigma_q}$*, adjusted by investor agreement via the factor* $\sqrt{\frac{1}{\rho}-1}$*:*

$$\mathcal{M} \geq \frac{\sigma_p}{\sigma_q} \times \sqrt{\frac{1}{\rho} - 1} \tag{13}$$

*Proof.* See Appendix A. □

**In-sample bounds.** Notice that although we express the bound in terms of population parameters, the identities used in deriving the bound all hold in sample as well. Hence we can express the bound using sample moments, given as:

$$\mathcal{M} \geq \frac{\hat{\sigma}_p}{\hat{\sigma}_q} \times \sqrt{\frac{1}{\hat{\rho}} - 1} \tag{14}$$

where $\hat{\sigma}_p$ and $\hat{\sigma}_q$ are the sample counterparts of price and flow volatilities, and $\hat{\rho}$ is the investor agreement of demand shifts within the sample period.

Moreover, the bound can be applied period by period, under the assumption that $\Delta q_{i,t}$ and $\Delta p_t$ have mean zero in a given period $t$ (which can be achieved by demeaning across $t$, assuming that means are stable):

$$\mathcal{M}_t \geq \frac{|\Delta p_t|}{\sqrt{\sum_{i=1}^{I} S_i \Delta q_{i,t}^2}} \times \sqrt{\frac{1}{\rho_t} - 1} \tag{15}$$

where $\rho_t \equiv \frac{(\sum_{i=1}^{I} S_i u_{i,t})^2}{\sum_{i=1}^{I} S_i u_{i,t}^2}$ is the investor agreement *in period t*.

### 2.5 Flow Volatility and Portfolio Turnover

The key input to our bound, flow volatility $\sigma_q$, is defined as the size-weighted average of investor-specific flow volatilities. Seemingly complicated, we show that it is closely related to the total trading activity from changes in investors' portfolios, which we term *portfolio turnover*. For a stock in a given quarter $t$, portfolio turnover is defined as the sum of the absolute values of quarter-on-quarter changes in positions of all investors, normalized by shares outstanding:

$$\text{Turnover}_t = \frac{\sum_i |\Delta Q_{i,t}|}{\bar{Q}} \tag{16}$$

where $\Delta Q_{i,t} = Q_{i,t} - Q_{i,t-1}$ is the change in position of investor $i$ from $t-1$ to $t$, and $\bar{Q}$ is total supply.

Portfolio turnover measures the (size-weighted) *mean absolute deviation* (MAD) of flows:

$$\mathbb{E}\big[\text{Turnover}_t\big] = \mathbb{E}\left[\sum_i S_i \frac{|\Delta Q_{i,t}|}{S_i \bar{Q}}\right] = \sum_i S_i \mathbb{E}\left[|\Delta q_{i,t}|\right]. \tag{17}$$

It mirrors the definition of flow volatility, $\sigma_q \equiv \sqrt{\sum_{i=1}^{I} S_i \mathbb{E}\left[(\Delta q_{i,t})^2\right]}$, but with an $\mathcal{L}_1$-norm rather than an $\mathcal{L}_2$-norm. For common distributions, the mean absolute deviation $\mathbb{E}\left[|\Delta q_{i,t}|\right]$ is proportional to the standard deviation $\sigma_{q,i}$ by a constant factor $\nu$ determined by the underlying distribution. For example, for normally distributed $\Delta q_{i,t}$, $\nu = \sqrt{\frac{\pi}{2}} \approx 1.25$. Empirically, Appendix Figure E.1 shows that portfolio turnover scaled by $\sqrt{\frac{\pi}{2}}$ and $\sigma_q$ are effectively equivalent with a cross-sectional correlation of around 0.9 and an OLS slope coefficient of 1.1. For this reason, we view the scaled portfolio turnover, $\sqrt{\frac{\pi}{2}}\text{Turnover}_t$, as an alternative (and more robust) estimator for $\sigma_q$. Formally,

$$\sigma_q^{\mathcal{L}_1} \equiv \sqrt{\frac{\pi}{2}}\mathbb{E}\left[\text{Turnover}_t\right].$$

When the scaling factor is unimportant, we also simply refer to $\sigma_q^{\mathcal{L}_1}$ as portfolio turnover.

Portfolio turnover is closely linked to total trading volume by construction. Index individual trades *within* period $t$ by $k$, and let $|\Delta Q_k|$ denote the size of trade $k$. Total trading volume in period $t$ is

$$\text{Volume}_t = \sum_{k \in t} |\Delta Q_k|. \tag{18}$$

For investor $i$, their net position change over $t$ can be expressed as the sum of all trades they participate in:

$$\Delta Q_{i,t} \;=\; \sum_{k\in(i,t)} s_{i,k}\,|\Delta Q_k| \qquad s_{i,k}\in\{-1,+1\}, \tag{19}$$

where $k \in (i,t)$ denotes that investor $i$ participates in trade $k$ during $t$, and $s_{i,k} = +1$ if $i$ is the buyer, and $-1$ if $i$ is the seller. We immediately have $|\Delta Q_{i,t}| \leq \sum_{k\in(i,t)} |\Delta Q_k|$: the net change in position is no greater than the total gross volume.

Summing over investors, we can construct an upper bound on the portfolio turnover using total trading volume:

$$\text{Turnover}_t = \frac{\sum_i |\Delta Q_{i,t}|}{\bar{Q}} \leq \frac{1}{\bar{Q}} \sum_i \sum_{k\in(i,t)} |\Delta Q_k| = \frac{2\text{Volume}_t}{\bar{Q}}. \tag{20}$$

The factor of 2 arises because the sum over investors counts each trade twice: once under the buyer and once under the seller. The equality holds if investors do not engage in round-trip trades within period $t$, i.e., each investor either only buys or only sells during period $t$: $s_{i,k}$ is constant over $k \in (i,t)$.

When the time window $t$ is sufficiently short, round-trip trades become negligible, allowing portfolio turnover to be approximated directly from total trading volume. Since volume data are far more readily available than holdings data, this enables analysis at high frequencies where round trips are less prevalent. Specifically, we can consider the following volume-based proxy for the flow volatility:

$$\sigma_q^{\text{Gross}} \equiv \sqrt{\frac{\pi}{2}} \times \frac{2\,\mathbb{E}[\text{Volume}_t]}{\bar{Q}}. \tag{21}$$

By construction, $\sigma_q^{\text{Gross}}$ converges to $\sigma_q^{\mathcal{L}1}$ from above as the measurement window shrinks to zero. At longer horizons, however, round-trip trades accumulate and mechanically inflate gross-volume-based measures, causing $\sigma_q^{\text{Gross}}$ to substantially overstate true portfolio turnover. As a result, $\sigma_q^{\text{Gross}}$ becomes an unreliable proxy for flow volatility over quarterly and annual windows. To avoid confusion, we henceforth refer to $\sigma_q$ as portfolio turnover and to $\sigma_q^{\text{Gross}}$ as gross turnover.

### 2.6 The Bound in the Multi-asset System

Our bound thus far applies to single assets, but real-world portfolio choice involves substitution across multiple assets. The existing literature emphasizes how ignoring cross-asset substitution biases price impact estimates: Chaudhary, Fu, and Li (2023) demonstrates that neglecting heterogeneous substitution patterns in bond markets leads to biased cross-sectional estimates. Haddad, He, et al. (2025) show that identifying aggregate elasticities requires time-series variation even when accounting for heterogeneous substitution patterns.

Since our bound relies on time-series variation, it avoids the cross-sectional bias identified by Chaudhary, Fu, and Li (2023). The bound remains valid—single-asset flow and return volatilities still capture the fundamental trade-off between price impact and investor agreement. However, both price impact and investor agreement acquire alternative interpretations in multi-asset settings, which we now explore.

The critical insight is that multi-asset demand systems can still be expressed as single-asset demand equations of the form in (2). We illustrate this through a concrete example.

**The single-asset representation of the two-asset system.** Let $n$ and $n'$ denote two substitutable assets. For ease of exposition, consider the case with homogeneous elasticities across investors – a general case with heterogeneous elasticities is discussed in Chaudhary, Fu, and Zhou (2024). Define the flow and price vectors as $\Delta\mathbf{q}_{i,t} \equiv (\Delta q_{i,t}(n), \Delta q_{i,t}(n'))^\intercal$, $\Delta\mathbf{p}_t \equiv (\Delta p_t(n), \Delta p_t(n'))^\intercal$, and $\mathbf{u}_{i,t} \equiv (u_{i,t}(n), u_{i,t}(n'))^\intercal$. The log-linear demand of investor $i$ is

$$\Delta\mathbf{q}_{i,t} = \Gamma\,\Delta\mathbf{p}_t + \mathbf{u}_{i,t}, \qquad \Gamma = \begin{pmatrix} -\zeta(n) & \zeta(n,n') \\ \zeta(n',n) & -\zeta(n') \end{pmatrix}, \tag{22}$$

where $\zeta(n)$ is the own-price elasticity for asset $n$, and $\zeta(n,n')$ is the cross-elasticity of demand for asset $n$ with respect to the price of asset $n'$.

Using subscript $S$ to denote the size-weighted aggregation, e.g., $\Delta q_{S,t}(\cdot) \equiv \sum_i S_i(\cdot)\,\Delta q_{i,t}(\cdot)$, market clearing gives:

$$\mathbf{0} = \Gamma\,\Delta\mathbf{p}_t + \mathbf{u}_{S,t}, \qquad \Rightarrow \qquad \Delta\mathbf{p}_t = -\,\Gamma^{-1}\,\mathbf{u}_{S,t}, \tag{23}$$

Inverting the elasticity matrix $\Gamma$, the own-price impact of a demand shift to asset $n$ is:

$$\mathcal{M}(n) = \frac{\partial\,\Delta p_t(n)}{\partial u_{S,t}(n)} = \frac{1}{\zeta(n)\,(1-\mathcal{Q}_{n\leftarrow n'}\,\mathcal{Q}_{n'\leftarrow n})} \tag{24}$$

where $\mathcal{Q}_{n\leftarrow n'}$ and $\mathcal{Q}_{n'\leftarrow n}$ are defined as

$$\mathcal{Q}_{n\leftarrow n'} := \frac{\zeta(n,n')}{\zeta(n')}, \qquad \mathcal{Q}_{n'\leftarrow n} := \frac{\zeta(n',n)}{\zeta(n)}. \tag{25}$$

We term these coefficients *demand pass-throughs*: $\mathcal{Q}_{n\leftarrow n'}$ measures how a unit demand shift for asset

$n'$ translates into an effective demand shift for asset $n$ through substitution.[10]

From the second row of the market-clearing condition (23), we can express the price change of asset $n'$ as a function of the price change of asset $n$ and the demand shift to asset $n'$:

$$\Delta p_t(n') \;=\; \frac{\zeta(n',n)}{\zeta(n')}\,\Delta p_t(n) \;+\; \frac{1}{\zeta(n')}\,u_{S,t}(n'). \tag{26}$$

Substituting (26) into the demand equation for asset $n$ yields the single-asset representation:

$$\Delta q_{i,t}(n) \;=\; -\underbrace{\zeta(n)\;(1-\mathcal{Q}_{n\leftarrow n'}\,\mathcal{Q}_{n'\leftarrow n})}_{\tilde{\zeta}(n)\,=\,1/\mathcal{M}(n)}\,\Delta p_t(n) \;+\; \underbrace{\mathcal{Q}_{n\leftarrow n'}\,u_{S,t}(n') \;+\; u_{i,t}(n)}_{\tilde{u}_{i,t}(n)}, \tag{27}$$

Since (27) mirrors the single-asset demand curve (2), Theorem 1 applies directly with identical construction. The differences lie in interpreting the bound's two key components.

First, while Theorem 1 continues to bound the own-price impact $\mathcal{M}(n)$, the price impact no longer equals the reciprocal of the own-price elasticity $\zeta(n)$; instead, it includes the amplification factor $(1-\mathcal{Q}_{n\leftarrow n'}\,\mathcal{Q}_{n'\leftarrow n})$. The distinction arises because price elasticity $\zeta(n)$ measures partial-equilibrium responses – how demand responds to price changes *with substitute prices held fixed.* In contrast, price impact $\mathcal{M}(n)$ captures the feedback loop from the general-equilibrium effects: a demand shift for asset $n$ moves not only its own price but also substitute prices, which recursively feed back into demand for asset $n$ itself.

Second, investor agreement $\rho$ now encompasses both agreement on asset-specific demand shifts $u_{i,t}(n)$ and agreement on substitution effects from the aggregate demand shift to substitutes $u_{S,t}(n')$. The latter enters asset $n$'s demand because it moves substitute prices, effectively acting as a common demand shift for asset $n$ through cross-asset substitution.

When substitution effects remain moderate (small pass-throughs $\mathcal{Q}_{\cdot,\cdot}$), the interpretive differences between single-asset and multi-asset settings are minor. However, strong substitution patterns require careful interpretation of the bound. Appendix C provides detailed analysis and numerical examples for such cases.

[10] Demand pass-throughs relate to cross-elasticities but are expressed in quantity units. While $\zeta(n,n')$ measures how a *price* change in $n'$ affects demand for $n$, dividing by $\zeta(n')$ converts this to how a *demand shift* in $n'$ affects demand for $n$. One crucial difference is that cross-elasticities are a partial-equilibrium concept, while demand pass-through depends on how the substitute price responds to the demand shift, and hence is intrinsically a general-equilibrium object.

# 3 Data and Empirical Facts

## 3.1 Data Sources and Variable Construction

**Data.** Our baseline empirical analyses are at the quarterly frequency. We first apply the bound at the individual stock level. We obtain quarterly institution-level share holdings $Q_{i,t}(n)$ from 1990 to 2024 from the Thomson Institutional Holdings Database (s34 file), where institutions are denoted by $i = 1, ..., I$, stocks are denoted by $n = 1, ..., N$, and the subscript $t$ indicates the report date of the 13F filing.[11] Further details can be found in Appendix D.1. Subsequently, we merge quarterly stock holdings with data on prices and fundamentals from CRSP, Compustat, and IBES. We restrict our sample to common ordinary shares (share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ (exchange codes 1, 2, and 3), that have (on average) at least 10 institutional holders and at least 30% observed institutional ownership.[12] $\Delta$ denotes quarterly changes. Ownership shares (size-weights) are denoted by $S_{i,t}(n) = \frac{Q_{i,t}(n)}{\bar{Q}_t(n)}$, where $\bar{Q}_t(n)$ are the total shares outstanding of the stock. Empirically, we do not observe the holdings of *all* investors, but are restricted by reported 13F filings. We therefore construct the trades of the residual sector that holds the remaining shares outstanding such that the trades of all investors sum to 0. Consequently, any share issuances not absorbed by institutions are recorded as trades by the residual investor sector.[13]

**Estimating volatilities.** As discussed in Section 2, our bound holds both in sample as well as period by period. We estimate both $\sigma_q(n)$ and $\sigma_p(n)$ in the time series for each stock using five-year backward-looking rolling windows, preventing our results to suffer from forward-looking bias. We estimate $\sigma_p(n)$ using the time-series volatility of quarterly stock returns. As described in Section 2.5, $\sigma_q(n)$ can either be measured directly as $\sqrt{\sum_{i=1}^{I} S_{i,t}\widehat{\text{Var}}(\Delta q_{i,t}(n))}$, the size-weighted average of investor-specific volatilities (the $\mathcal{L}_2$ norm), or approximated using portfolio turnover $\sqrt{\frac{\pi}{2}}\hat{\mathbb{E}}\left[\text{Turnover}_t(n)\right]$ (the $\mathcal{L}_1$ norm). We construct both measures and find similar results. We favor portfolio turnover for several reasons. First, it is straightforwardly constructed and closely linked to gross trading volume. Second and more

[11] In the main text, we use holdings at the institution level (e.g., BlackRock as a single entity rather than as individual funds) to achieve the most comprehensive coverage. Since holdings are aggregated across funds within the same asset manager, transactions among funds within the same institution are not observed at this level, which could potentially lead to an underestimation of portfolio turnover. However, in Appendix D.1, we show that portfolio turnover computed at the mutual fund level is very close to that at the institution level, suggesting that within-fund-family trades are negligible.

[12] All results are robust to alternative cut-offs.

[13] All results in the paper are robust to omitting the residual sector and constructing $\bar{Q}_t(n)$ (and the corresponding size weights) as the sum of institutional shares held. However, we prefer to construct the residual sector as doing so accounts for trades between the institutional sector as a whole and the residual investor sector, which would be omitted otherwise.

importantly, $\mathcal{L}_2$ norms, such as the standard deviation, are susceptible to outliers – a common feature in flow data – while $\mathcal{L}_1$ norms, such as the mean absolute deviation, are more robust estimators of statistical dispersion in the presence of fat tails (due to frequent extensive margin trades).

Unlike $\sigma_q$ and $\sigma_p$, which are directly observable from trade and price data, investor agreement $\rho$ is inherently unobserved. To that end, we first present results that are agnostic about the level of investor agreement. Later in Section 4.2, we present and discuss different strategies of how to empirically measure $\rho$.

The top panel of Table 1 reports $\sigma_p(n)$ and $\sigma_q(n)$ (both measured via $\mathcal{L}_1$ and $\mathcal{L}_2$ norms). The average share in our sample has a quarterly return volatility $\sigma_p$ of 22%. The average $\sigma_q$ constructed from portfolio turnover is 25%. The 5th percentile, median, and 95th percentile are given by 7%, 23%, and 50%, respectively. In contrast, the $\mathcal{L}_2$ measure of $\sigma_q$ is distributed very similarly with a slightly higher average of 30% and the 5th percentile, median, and 95th percentile given by 10%, 30%, and 53%, respectively. The ratio of return volatility to portfolio turnover (hereafter, p/q volatility ratio) equals 1.16 for the average stock. However, there exists considerable variation in this ratio as can be seen from the 5th and 95th percentiles, which equal 0.36 and 3.05, respectively.

Finally, Table 1 also reports moments of the distributions of institutional ownership and trading volume. For example, the average share is held by about 200 institutions with an average institutional ownership share of 60%. Notably, all our main results are robust to restricting the sample to stocks for which institutional ownership is higher than 90%.

### 3.2 Portfolio Turnover and Gross Trading Volume

Because our baseline portfolio turnover measure relies on institutional holdings data, one might be concerned that the high p/q volatility ratio is an artifact of our particular sample construction – that missing trades in the database lead us to significantly underestimate true flow volatility $\sigma_q$. We address this concern with several pieces of evidence.

To ensure we capture all transactions occurring on exchanges, we measure portfolio turnover using gross turnover from CRSP *at the daily frequency.* As discussed in Section 2.5, at short horizons, there are fewer round-trip trades and gross turnover provides a reasonable approximation of net portfolio turnover, $\sigma_q^{\text{Gross}} \approx \sigma_q$. At this frequency, we find a p/q volatility ratio similar to or even higher than our quarterly baseline: average daily return volatility is approximately 2%, while gross turnover $\sigma_q^{\text{Gross}}$ is around 1%, yielding a p/q volatility ratio of approximately 2. Moreover, because round-trip trades

Table 1: **Summary Statistics**
The table summarizes the distribution of the key variable inputs for deriving the price impact bounds over the cross-section of US equities. The top panel reports the volatility of returns $\sigma_p$ and the volatility of flows $\sigma_q$, both explicitly computed via size-weighted investor-specific volatilities, and the $\mathcal{L}_1$ approximation from portfolio turnover. The volatilities are computed over 5-year rolling windows. The bottom panel reports the number of investors holding each stock, institutional ownership, investor concentration defined as $\sum_i S^2_{i,t}(n)$, and gross trading volume (from CRSP) relative to shares outstanding.

| | Mean | VW Mean | Std | 5th Pctl. | Median | 95th Pctl. |
|---|---|---|---|---|---|---|
| *Volatilities of Flows and Returns* | | | | | | |
| Return Volatility $\sigma_p$ | 0.22 | 0.15 | 0.15 | 0.09 | 0.19 | 0.47 |
| Flow Volatility $\sigma_q(\mathcal{L}_2)$ | 0.30 | 0.29 | 0.13 | 0.10 | 0.30 | 0.53 |
| Portfolio Turnover $\sigma_q(\mathcal{L}_1)$ | 0.25 | 0.19 | 0.13 | 0.07 | 0.23 | 0.50 |
| Volatility Ratio $\sigma_p/\sigma_q$ | 1.16 | 0.92 | 1.33 | 0.36 | 0.81 | 3.05 |
| *Ownership and Trade Statistics* | | | | | | |
| Number of Institutional Holders | 201.86 | 1267.32 | 275.70 | 14.00 | 123.00 | 659.00 |
| Institutional Ownership | 0.60 | 0.68 | 0.26 | 0.15 | 0.62 | 0.99 |
| Ownership Concentration (HHI) | 0.23 | 0.15 | 0.21 | 0.04 | 0.16 | 0.67 |
| Gross Volume/Shrout | 0.46 | 0.45 | 0.55 | 0.06 | 0.31 | 1.35 |

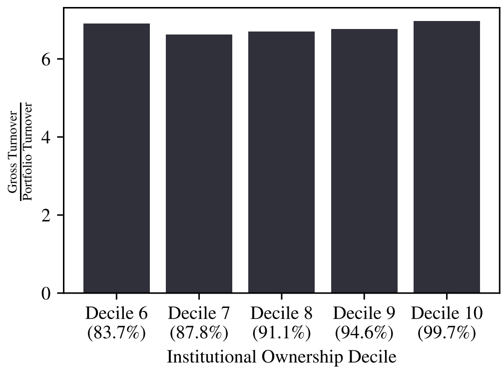
occur even within a single day, gross turnover overstates true portfolio turnover, implying the actual p/q volatility ratio at the daily frequency is even higher. These findings suggest that the high p/q volatility ratio is not an artifact of missing trades in our institutional holdings data. In Section 6.1, we further analyze how the p/q volatility ratio varies across different horizons and sample periods.

At longer horizons, round-trip trades accumulate throughout the period, causing gross turnover to substantially overstate portfolio turnover, $\sigma_q^{\text{Gross}} \gg \sigma_q$. Gross turnover averages nearly 120%, which underlies the common perception that markets exhibit unusually high trading activity. In contrast, portfolio turnover is only 20% on average. Because of the large discrepancy between the two measures at quarterly or longer horizons, gross turnover is no longer informative for constructing the bound. Nevertheless, it serves as a useful qualitative benchmark for evaluating our holdings-based measures.[14]

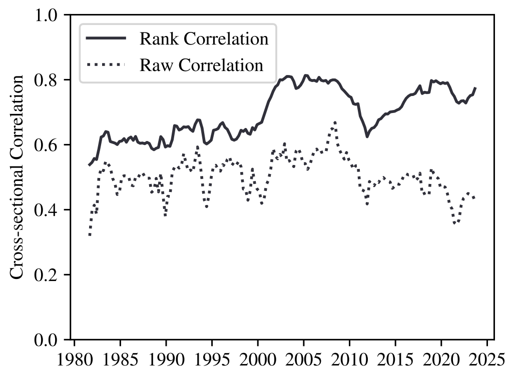
[14] Dissecting the difference between gross turnover and institutional portfolio turnover and analyzing the effects of high-frequency intermediation for long-term asset pricing is beyond the scope of this paper, but an exciting avenue for future research. In follow-up work, we link the long-term asset pricing implications of portfolio turnover and the short-term microstructural implications of high-frequency trading volume. We show that the market participants that have entered since 1980 – such as high-frequency market makers, ETF authorized participants, algorithmic trading firms, and (mobile) retail traders – have contributed to the surge in trading volumes and a decline of short-term price impact, but did not help absorbing long-term demand shifts.

Figure 1: **Portfolio Turnover versus Gross Turnover**
Panel a) of the figure plots the ratio of gross turnover $\sigma_q^{\text{Gross}}$ and portfolio turnover $\sigma_q$ for groups of stocks sorted by institutional ownership. $\sigma_q^{\text{Gross}}$ is the flow volatility obtained from CRSP trading volume (as opposed to institutional portfolio turnover). Average institutional ownerships for each decile are reported in brackets. Panel b) of the figure plots the quarterly (rank) correlation of $\sigma_q^{\text{Gross}}$ and $\sigma_q$ in the cross-section of stocks. We report annual averages of quarterly correlations.

(a) $\sigma_q^{\text{Gross}}/\sigma_q$ by Institutional Ownership




(b) Correlation: $\sigma_q^{\text{Gross}}$ vs. $\sigma_q$




We first verify that the large gap between gross turnover and portfolio turnover is not due to unobserved portfolio rebalancing in the institutional holdings data. Panel a) of Figure 1 plots the ratio of gross turnover $\sigma_q^{\text{Gross}}$ to portfolio turnover $\sigma_q$ across stocks sorted by institutional ownership. Notably, the ratio remains essentially constant across ownership groups, indicating that unobserved portfolio adjustments do not explain the gap. Even in the top decile – where average institutional ownership reaches 99.7% – gross turnover remains approximately six times larger than portfolio turnover. All our main results are robust to restricting the sample to stocks with high institutional ownership.[15]

Despite differing substantially in magnitude, portfolio turnover and gross turnover exhibit similar cross-sectional patterns. Panel b) of Figure 1 shows that despite a six-fold difference in levels, the two measures are highly correlated in the cross-section, with rank correlations reaching approximately 80% in recent periods. This strong correlation indicates that both measures reflect similar underlying economic activity, but gross turnover is mechanically inflated by intra-period round-trip trades.

A final concern is that large asset managers may net trades internally within fund families: when one fund sells a stock while another fund in the same family buys it, the manager may net the transaction internally rather than routing it through an exchange. If pervasive, even gross turnover could underestimate total trading activity. However, we find that such internal netting has minimal

[15] Complementary evidence from household data further confirms that households exhibit even lower portfolio turnover than institutional investors. Using household holdings data, Gabaix, Koijen, et al. (2025) measure risk transfer – defined as the percent change in market risk exposure for a group of investors over a given period, a concept closely related to portfolio turnover at the aggregate market level. They find that quarterly risk transfer is only 0.65% for household groups, far smaller than the 6% portfolio turnover observed for institutional investors at the aggregate market level (reported in Figure 7 below).

impact on our measurements. In Appendix D.1, we disaggregate 13F managers into their constituent mutual funds and ETFs, showing that portfolio turnover computed at the fund level is only marginally larger than at the institutional level. This suggests that within-fund-family netting is negligible.

# 4 The Price Impact Bound

## 4.1 The Price Impact Bound under Varying Levels of Investor Agreement

As discussed above, in a first step, we evaluate the price impact bounds without taking a stance on the level of investor agreement $\rho$. In particular, we document the bounds $\mathcal{M}(\rho)$ as a function of $\rho$ for U.S. equities. That is, using stock-level return volatility, $\sigma_p$, and portfolio turnover, $\sigma_q$, constructed as described in the previous section, we compute the bound $\mathcal{M}(\rho)$ for each stock while allowing $\rho$ to vary between 0 and 1. Panel a) of Figure 2 plots the distribution of the lower bounds of price impact for individual U.S. stocks. In contrast, Panel b) plots the distribution of the upper bounds on aggregate elasticity, i.e., the inverse of the price impact bounds.

Figure 2: **Price Impact Bounds under Varying Agreement $\rho$**
The figure plots the price impact bound for a given level of investor agreement $\rho$. Panel a) plots the lower bound on the price impact $\mathcal{M}(\rho)$ as a function of $\rho$, for the average US stock, as well as the top and bottom 10% of stocks with the highest and lowest p/q volatility ratio $\frac{\sigma_p}{\sigma_q}$. The lower bound on price impact can be inverted to obtain an upper bound on the aggregate (size-weighted) elasticity. Panel b) plots the upper bound on the aggregate elasticity $\zeta_S(\rho)$ for US stocks.

(a) Price Impact Bound $\mathcal{M}(\rho)$ (b) Elasticity Bound $\zeta_S(\rho)$

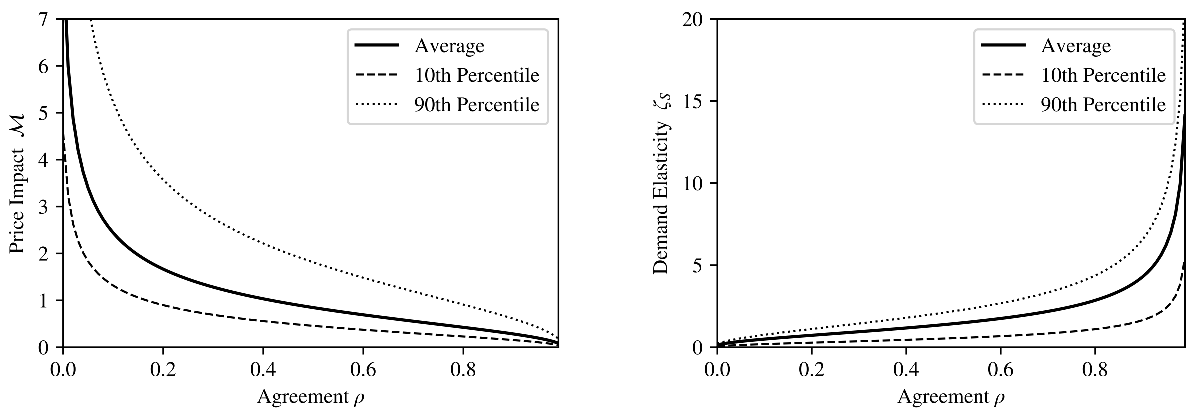



Figure 2 shows that a high p/q volatility ratio can be consistent with perfectly elastic markets that feature a close-to-zero price impact. However, such coexistence requires a high degree of agreement among investors, implying that their demand shifts are almost perfectly correlated. Note that the average level of the p/q volatility ratio $\frac{\sigma_p}{\sigma_q}$ is about 1. That is, for a 1% demand shift to move prices less than 0.1% ($\mathcal{M} < 0.1$), investor agreement must exceed 99%. In other words, the empirical level of the p/q volatility ratio can only be reconciled with elastic markets if investors are homogeneous to an extremely high degree. Put differently, under reasonable levels of investor disagreement, price impact will exceed 0.1%. Generally, the bounds are more stringent as investor agreement decreases ($\rho \to 0$).

### 4.2 Measuring Investor Agreement

Without an explicit measure of investor agreement, $\rho$, the lower bound of price impact cannot be determined. However, as can be seen from Figure 2 the bound is relatively flat when $\rho$ lies in the medium range, e.g., between 0.2 and 0.8. In this region, the bound varies predominantly due to variation in the p/q volatility ratio in our application to the cross-section of U.S. stocks. Panel a) of Appendix Figure E.2 reinforces this conclusion more formally by plotting the partial derivative of the bound with respect to $\rho$. The derivative is small in absolute terms in a large surrounding neighborhood of $\rho = 0.5$, but grows significantly for extreme degrees of agreement/disagreement, i.e., as $\rho$ approaches 1 or 0. The fact that the partial derivative is mostly small implies that to differentiate between models with $\mathcal{M} = 1$ versus models with $\mathcal{M} = 0.5$ using our bound, we require a highly precise estimate of $\rho$. However, rejecting the null hypothesis that $\mathcal{M} < 0.1$, as implied by most canonical frictionless models, merely requires showing that $\rho < 0.99$. Arguably, this is a much lower hurdle to cross given the extensive literature on heterogeneity in preferences and beliefs among investors. Therefore, rather than trying to provide a precise estimate of $\rho$, our first objective is to establish that $\rho$ is unlikely to be close to either 0 or 1. In this case, the factor $\sqrt{\frac{1}{\rho} - 1}$ is relatively close to 1 and hence the simple p/q volatility ratio is a close proxy for the actual price impact bound.

Note that common portfolio-based measures of disagreement, such as short interest and active share, cannot directly inform us about investor agreement, as these measures are endogenous to prices and thus already contain information about elasticities – the very quantity we seek to measure. To estimate $\rho$ from the holdings data, we need to impose more structural assumptions on elasticities and the demand shifts. For example, one can impose a logit demand system in the cross section and recover the model-implied agreement (e.g., Koijen and Yogo, 2019) – our Appendix D.4 represents one such exercise; alternatively, one can impose a factor structure on demand shocks and identify them using granular instrument variables (e.g., Gabaix and Koijen, 2021; Chaudhary, Fu, and Zhou, 2024).

Opting for a reduced-form approach in the main text, we present a different method inspired by the large literature on investor beliefs (Dahlquist and Ibert, 2024): we estimate $\rho$ directly from survey data using analyst agreement as a proxy for investor agreement. This approach is almost model-free, as it does not require imposing any specific covariance structure on the underlying demand shifts. However, it does require that the estimated $\rho$ for analysts is "portable" and, thus, accurately reflects the $\rho$ of investors. Importantly, we do not assume that investors and analysts are the same agents – only that the cross-sectional dispersion in analyst forecasts is a reasonable proxy for the heterogeneity in investors' demand shifts. Notably, analysts tend to operate within a relatively homogeneous professional environment, and belief disagreement captures only one aspect of broader investor heterogeneity. As such, the limited dispersion in analyst expectations likely overstates the degree of correlation in demand shifts among the full set of investors.

Since analysts submit forecasts across different horizons – from one-quarter ahead to long-term growth rates – and investors care about the total discounted cash flows when trading stocks, we estimate analyst agreement at different horizons. To be consistent with our theoretical framework, we focus on agreement in quarterly forecast updates from Institutional Broker Estimates System (I/B/E/S) stock analysts. Specifically, let $\Delta f_{i,t}^h(n)$ denote the update made by analyst $i$ in period $t$ to the earnings per share (EPS) forecast of firm $n$ for horizon $h$. We then estimate analyst agreement $\rho_{EPS}^h(n)$ for each stock $n$ and forecast horizon $h$ as the adjusted $R^2$ from regressing $\Delta f_{i,t}^h(n)$ on time fixed effects:[16]

$$\Delta f_{i,t}^h(n) = \gamma_t + \epsilon_{i,t}^h(n) \quad \text{for each } n \text{ and } h, \tag{28}$$

where $\gamma_t$ denotes time fixed effects. We estimate Equation (28) for horizons ranging from one-quarter ahead to three-quarter ahead, as well as long-term growth rates (LTG). The details of the sample construction and estimation procedures can be found in Appendix D.3.

Table 2: **Summary Statistics of $\rho$ Estimated from Earnings Forecast Updates**
The table reports the distribution of investor agreement $\rho$ estimated from analyst forecast updates using Equation (28). For each stock and forecast horizon, $\rho$ is computed as the adjusted $R^2$ from regressing analyst forecast updates on time fixed effects. 1Q, 2Q, and 3Q refer to one-quarter ahead, two-quarter ahead, and three-quarter ahead earnings per share (EPS) forecasts, respectively. LTG refers to long-term growth forecasts.

| Horizon | Number of Firms | Mean | 5th pctl. | Median | 95th pctl. |
|---|---|---|---|---|---|
| 1Q | 754 | 0.53 | 0.16 | 0.56 | 0.80 |
| 2Q | 669 | 0.47 | 0.11 | 0.48 | 0.76 |
| 3Q | 585 | 0.41 | 0.07 | 0.40 | 0.75 |
| LTG | 366 | 0.29 | 0.00 | 0.26 | 0.72 |

Table 2 reports the cross-sectional distribution of $\rho^h(n)$ for different forecast horizons. Intriguingly,

[16]We first demean forecast updates across time within each analyst, ensuring that the total variation in the regression excludes heterogeneity in average forecast updates. See Appendix D.3 for more details.

analyst agreement exhibits a clear term structure across forecast horizons: as the horizon increases, analysts increasingly disagree with each other. This pattern is intuitive – forecast uncertainty grows with the forecasting horizon, and fewer reliable common signals are available for analysts to anchor their expectations. Since a stock's value reflects discounted cash flows across all horizons, investors' demand shifts incorporate innovations to expected cash flows possibly across all horizons. Consequently, estimates derived from forecasts for one quarter and long-term growth can be interpreted as upper and lower bounds of investor agreement originating from cash flow expectations.

For stocks in the United States, the average update in one-quarter ahead earnings per share forecasts across analysts explains approximately 57% of the total variation in EPS updates. At this level of investor agreement ($\rho = 57\%$), we obtain a (value-weighted) average stock-level price impact of 0.75. In contrast, the average update in long-term growth forecasts explains only 32% of the total variation in LTG updates, implying a price impact of 1.25. Across all measures of investor agreement, we rarely observe values of $\rho$ exceeding 80%, suggesting that for the vast majority of stocks, price impact exceeds 0.5 and price elasticity is below 2.

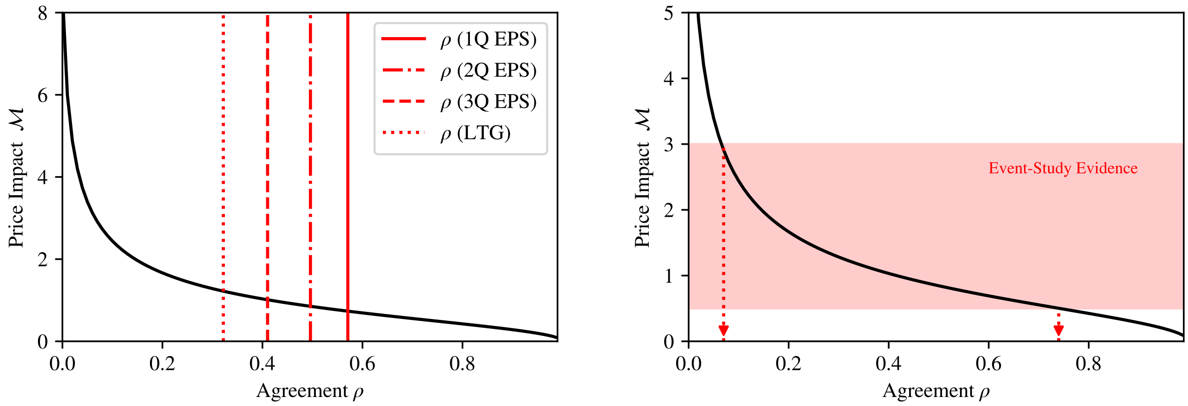
**Event-Study Implied Agreement.** Alternatively, we can compare our estimates of investor agreement from the I/B/E/S data against the investor agreement *implied* by event-study estimates of price impact. To that end, we take the empirical estimates of $\mathcal{M}$ at face value and use Equation (12) to impute $\rho$. Panel a) of Figure 3 reports average $\rho$ based on survey data, along with the average price impact bound as a function of $\rho$. We plot the average $\rho$ obtained from 1, 2, and 3-quarter ahead EPS forecast updates, as well as LTG updates. Panel b) documents the implied $\rho$ based on price impact estimates from the literature. For the range of price impacts found in event studies (such as stock index inclusions, mutual fund flow-induced trades, and dividend reinvestments) our bound implies that investor agreement $\rho$ should roughly lie between 0.1 and 0.75. Notably, all our estimates from the I/B/E/S data are well within this range.

**Investor Agreement Implied from Structural Models.** Last, in Appendix D.4 we examine the investor agreement implied by a structural asset pricing model designed to match both prices and investor-level holdings data. To this end, we use the model by Koijen and Yogo (2019) and estimate the stock-level agreement implied by the demand curves within their framework. We again confirm that $\rho(n)$ is not pathologically high. The average $\rho$ implied by logit demand lies between 0.22 and

0.37.[17]

Figure 3: **Investor Disagreement: IBES versus Event Studies**
Panel a) plots the average $\rho$ from survey data along with the stock-level price impact bound as a function of $\rho$ for the average stock. We plot the average $\rho$ obtained from 1, 2, and 3-quarter ahead EPS forecast updates, as well as LTG updates. Panel b) plots the investor agreement implied from the range of price impacts found in event studies. The dotted lines indicate the implied investor agreement by the event-study range.

(a) Average $\rho$ from Survey Data (b) Implied $\rho$ by Event-Study Literature




## 4.3 Stock-Level Price Impact Bounds

Next, we apply our survey-based estimates of investor agreement to obtain a lower bound on the price impact for each individual stock as follows:

$$\mathcal{M}_{\text{EPS}}(n) \equiv \frac{\sigma_p(n)}{\sigma_q(n)} \sqrt{\frac{1}{\rho_{\text{EPS}}(n)} - 1} \tag{29}$$

All of the following results are robust to using any of the four forecast-horizon specific estimates of $\rho$ derived from the I/B/E/S data in our calculations of the lower bound. However, to maximize the cross-sectional sample size, we rely on $\rho$ estimated based on one-quarter ahead EPS forecasts in our baseline results.

As discussed earlier, the EPS-based price impact bound is imperfect, as it ignores investor disagreement along many other dimensions. Moreover, for values of $\rho$ in the neighborhood of 0.5, the term $(\sqrt{\frac{1}{\rho} - 1})$ is close to 1 in magnitude and relatively insensitive to changes in $\rho$. Therefore, we also consider an approximate price impact $\tilde{\mathcal{M}}(n)$ defined as the p/q volatility ratio, implicitly assuming

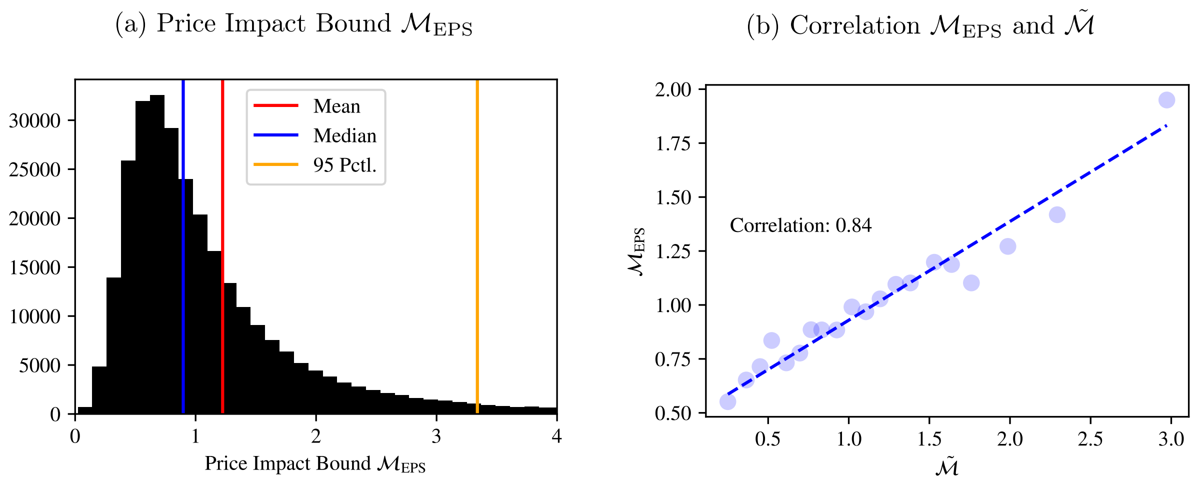
[17] The $\rho$ obtained from logit demand can only inform our bounds to a limited extent, as it requires assuming that logit elasticities from portfolio holdings in levels capture quarterly flow elasticities, which may be violated if investors are inert (Beck, 2022).

that $\rho(n) = 0.5$ for all stocks $n$. Formally,

$$\tilde{\mathcal{M}}(n) \equiv \frac{\sigma_p(n)}{\sigma_q(n)}. \tag{30}$$

When exploring beyond event studies, we refer to the p/q volatility ratio $\tilde{\mathcal{M}}(n)$ as "approximated price impact", or simply "price impact" when there is no ambiguity. In all our empirical tests, we report results for both $\mathcal{M}_{\text{EPS}}(n)$ and $\tilde{\mathcal{M}}(n)$.

Figure 4: **Implied Price Impact for US Equities**
The figure plots the distribution of price impact for the cross-section of US stocks. Panel a) plots the distribution of $\mathcal{M}_{\text{EPS}}(n) \equiv \frac{\sigma_p(n)}{\sigma_q(n)}\sqrt{\frac{1}{\rho_{\text{EPS}}(n)} - 1}$. We use our baseline measure of investor agreement $\rho$ extracted from EPS forecast updates $\rho_{\text{EPS}}$. When $\rho_{\text{EPS}}$ is missing for a given stock, we compute $\mathcal{M}_{\text{EPS}}$ using the cross-sectional average $\rho$ in our sample. Panel b) plots the correlation between $\mathcal{M}_{\text{EPS}}$ and the simple p/q volatility ratio $\tilde{\mathcal{M}} = \frac{\sigma_p}{\sigma_q}$ for stocks with observed $\rho_{\text{EPS}}$.




Panel a) of Figure 4 plots the distribution of the price impact bound $\mathcal{M}_{\text{EPS}}(n)$. For the average stock, the lower bound on the price impact is around 1. The top 5% of stocks have bounds exceeding 3.[18] Overall, there is considerable heterogeneity in the bound across stocks which we will explore in the next section. Importantly, the magnitudes of our bounds are consistent with empirical reduced-form evidence from index inclusions (e.g., Shleifer, 1986), mutual fund flow-induced trades (e.g., Lou, 2012), benchmarking intensity (e.g., Pavlova and Sikorskaya, 2023), and dividend reinvestments (e.g., Schmickler, 2020). Our bounds highlight that low demand elasticities are not an artifact of unique event studies but are instead a pervasive fact that can be directly inferred from the high p/q volatility ratio and the amount of investor disagreement in the market.

Finally, Panel b) of Figure 4 graphically illustrates the very high cross-sectional correlation between

[18] The distribution of the approximated price impact $\tilde{\mathcal{M}}(n)$, is very similar in shape and magnitudes.

$\tilde{\mathcal{M}}(n)$ and $\mathcal{M}_{\mathrm{EPS}}(n)$ of 84%. Relatedly, Panel b) Appendix Figure E.2 decomposes the cross-sectional variation in $\mathcal{M}_{\mathrm{EPS}}(n)$ and shows that $\rho$ plays a minor role relative to $\sigma_q$ and $\sigma_p$. [19]

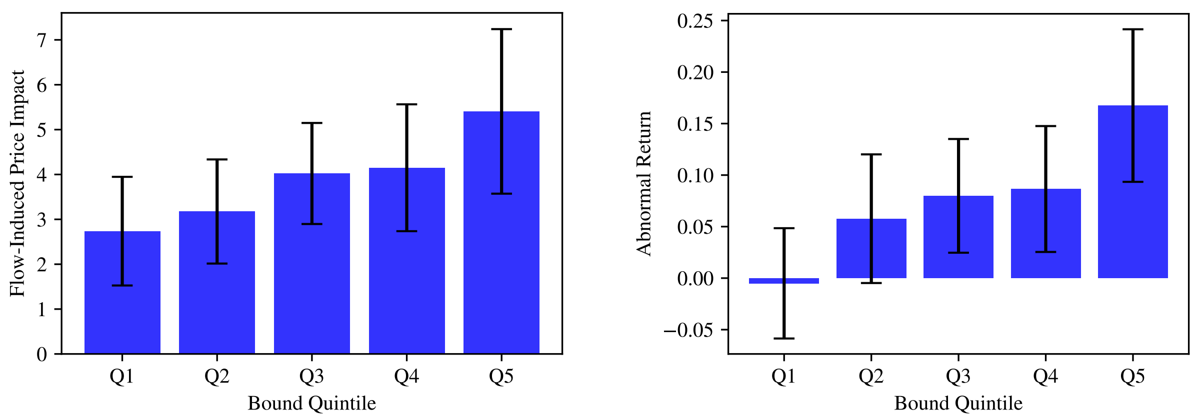
# 5 Empirical Relevance of the Stock-Level Bounds

Our bounds are particularly valuable in settings where empirical estimates are unavailable or difficult to obtain. For instance, identifying a source of plausibly exogenous demand shifts to credibly estimate the price impact for broad portfolios, such as the total U.S. equity market, is challenging. Similarly, estimating asset-level price impact is challenging because much of the carefully identified event-study evidence relies on cross-sectional variation and, thus, obtains pooled estimates across assets.

However, to trust our model-implied bounds in such a context, it is crucial to verify that the bounds align well with the empirical evidence from settings with credible identification strategies. To that end, we focus on two of the most widely used and verified event studies in empirical asset pricing. Mutual fund flow-induced trades and index inclusions. In particular, we test whether these (plausibly) exogenous demand shifts imply larger price changes for stocks with a higher price impact bound, $\mathcal{M}$.

Figure 5: **Validation: S&P 500 Inclusions and Flow-Induced Trades**
The figure summarizes the empirical validation of our bounds. Panel a) plots the coefficient of regressing quarterly stock-returns onto flow-induced trades (FIT) interacted with quintile dummies of our price impact bound. Panel b) plots the coefficient of regressing (signed) abnormal event returns during S&P 500 index reconstitutions onto quintile dummies of our price impact bound. When $\rho_{\mathrm{EPS}}$ is missing for a given stock, we compute $\mathcal{M}_{\mathrm{EPS}}$ using the cross-sectional average $\rho$ in our sample. We report 95% confidence intervals using standard errors clustered by date.

(a) Mutual Fund Flow Induced Trades (b) S&P 500 Inclusions/Deletions




[19] As discussed in Section 4.2, more formally, the reason for the minor role of investor agreement is that the derivative $\frac{\partial \mathcal{M}}{\partial \rho} = -\frac{\mathcal{M}}{2\,\rho\,(1-\rho)}$ is small as long as $\rho$ does not take extreme values.

### 5.1 Flow-induced trades

Following Coval and Stafford (2007), Lou (2012), and Edmans, Goldstein, and Jiang (2012), flow-induced trades by mutual funds (FIT) have been a widely used source of (plausibly) exogenous variation in demand. We follow the construction of flow-induced trades by Lou (2012) and relegate details to the Appendix D.5. To test whether stocks with higher price impact bounds have higher FIT returns, we interact FIT with $\mathcal{M}_{\text{EPS}}$. We then run panel regressions of quarterly stock returns onto FIT, the interaction of FIT with our bounds, and time fixed effects. As expected, the impact of flow-induced trades is significantly larger for stocks with higher price impact bounds as evidenced by the positive and statistically significant coefficient on the interaction term. Moreover, we sort the stocks into quintiles based on $\mathcal{M}_{\text{EPS}}$ and estimate the flow-induced price impact for each quintile by interacting FIT with quintile dummies. Panel a) of Figure 5 plots the results graphically and Appendix Table E.1 reports the results numerically. In line with our theoretical predictions, price impact estimates increase monotonically from the lowest to the highest price impact bound quintile. For example, the flow-driven price impact for the top quintile of stocks is about twice as large as in the bottom quintile.

### 5.2 Index Inclusions

Following Shleifer (1986) and Harris and Gurel (1986), an extensive body of literature investigates the average (abnormal) return around index inclusions and exclusions.[20] Index reconstitutions imply large uninformed demand shifts for affected securities, stemming from passive index trackers who mechanically buy the included and delete the excluded stocks from their portfolios. Relying on the data provided by Greenwood and Sammon (2025) on abnormal event returns and S&P 500 reconstitutions, we find an average abnormal event return of 8%. However, there is considerable variation in event returns with the cross-sectional standard deviation being equal to 12%. Similar to Section 5.1, we examine whether stocks with higher $\mathcal{M}_{\text{EPS}}$ experience significantly higher abnormal event returns. We find that our price impact bounds are highly statistically significantly related to abnormal event returns. In other words, stocks with high bounds have significantly higher (lower) returns when included in (excluded from) the S&P 500. As for flow-induced trades, we sort the included and excluded stocks into quintiles by their price impact bound and regress event returns onto the quintiles. Greenwood and Sammon (2025) find that index returns from announcement to effective reconstitution have declined over time, likely because investors increasingly front-run inclusions ahead of the announcement, spread-

[20]Among others, Petajisto (2011), Madhavan (2003), Chang, Hong, and Liskovich (2015), Pavlova and Sikorskaya (2023)

ing the effect over a longer window. We therefore focus on the pre-2000 period, when the average index effect was strongest. We also report the results for the whole sample period, which are quantitatively and qualitatively unchanged, but statistically weaker. Panel b) of Figure 5 plots the results graphically and Appendix Table E.2 reports the results numerically. As before, abnormal returns are increasing when moving from the lowest to the highest price impact bound quintile.

Lastly, we confirm that the ability of our bounds to price persistent demand shifts is not subsumed by standard high-frequency liquidity measures, which rely on gross trading volume rather than portfolio turnover. In particular, we use two alternative measures: the ratio of return volatility to gross turnover $\sigma_p/\sigma_q^{\text{Gross}}$ and the Amihud (2002) illiquidity measure. Appendix Tables E.3 and E.4 repeat the FIT and S&P500 inclusion regressions for these alternative measures. Importantly, the measures based on gross turnover rather than portfolio turnover do *not explain* the abnormal returns due to demand shocks. This suggests that – beyond simply inflating portfolio turnover due to round-trip trades – gross trading volume is less suited to measure *long-term* liquidity provision.

# 6 Exploring the Bounds Beyond Event Studies

The previous section documented that our bounds are empirically relevant when measuring long-term price impact of investor-specific demand shifts. Based on this evidence, we next explore the cross-sectional variation of our measures in different settings. To do this, we rely on our approximated price impact $\tilde{\mathcal{M}}$, whenever there is no suitable measure of investor agreement $\rho$ available, for example, due to limited time-series variation or lack of estimates of $\rho$ for aggregated portfolios.

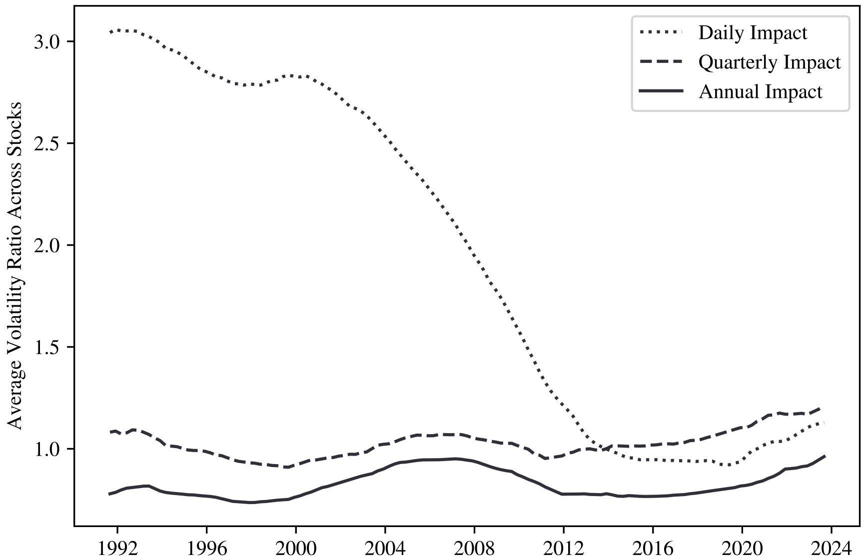
## 6.1 Price Impact Bound at Different Horizons

A natural feature of financial markets is a decreasing price impact at longer horizons. This pattern is consistent with long-term investors being more willing to bear long-term risks, accepting lower compensation for absorbing risks from higher-frequency traders who initially take the other side of a demand shift (Duffie, 2010). Decreasing price impact, therefore, implies that each layer of intermediation is compensated for providing liquidity. Instead, increasing price impact over time would imply that liquidity providers lose money on average as mispricing amplifies. Our bounds allow testing the extent to which price impacts decrease at lower frequencies and how the relationship between high- and low-frequency impact has evolved over time.

To this end, we construct portfolio turnover and return volatility at different horizons, denoted by $\sigma_{q,H}$ and $\sigma_{p,H}$, where $H = D, Q, Y$ corresponds to daily, quarterly, and yearly measures, respectively. Return volatility at these frequencies is straightforward to compute. Portfolio turnover at lower frequencies (e.g., quarterly or annual) is also easily constructed by measuring changes in portfolio holdings relative to shares outstanding and summing their absolute values. At the daily frequency, we proxy portfolio turnover $\sigma_{q,D}$ using daily gross turnover $\sigma_{q,D}^{\text{Gross}}$, as discussed in Section 2.5. This approach abstracts away from intra-day round-trip trades, which are significant due to market making and high-frequency trading. Because daily gross turnover overstates true daily net portfolio turnover, our measure is upward-biased. This bias makes the resulting price impact $\sigma_{p,D}/\sigma_{q,D}$ a conservative (lower-bound) estimate: if the true $\sigma_{q,D}$ is lower, the true price impact would be higher.

We construct price impact $\tilde{\mathcal{M}}_H(n) = \frac{\sigma_{p,H}(n)}{\sigma_{q,H}(n)}$ for every stock at the daily, quarterly, and annual level. Figure 6 plots the cross-sectional average for each horizon over time.

Figure 6: **Price Impact at Different Horizons**
The figure plots the stock-level price impact $\tilde{\mathcal{M}}_H(n) = \frac{\sigma_{p,H}(n)}{\sigma_{q,H}(n)}$ for the average stock from 1990 to 2024. We construct $\tilde{\mathcal{M}}_H(n)$ using portfolio turnover and return volatility at the quarterly and annual frequencies. For the daily frequency, we use gross turnover as a proxy for portfolio turnover. We plot ten-year rolling averages of price impact for visual clarity. The underlying (unaveraged) time series are reported in Figure E.3 in the Appendix.




First, consistent with Beck (2022), price impact decreases monotonically at longer horizons. In 2000, the average daily price impact was over twice as large as the quarterly impact, which in turn was 50% larger than the annual impact.[21]

Second, while daily price impact has decreased considerably over our sample period, quarterly and

[21] Note that, because daily price impact is computed using gross turnover (rather than portfolio turnover), it represents a lower bound on the true daily volatility ratio.

annual price impacts have remained largely flat. This pattern suggests that while markets have become more effective at absorbing demand shocks in the short run, their ability to accommodate long-term shifts has remained largely unchanged. Our focus in this paper lies on the asset pricing implications of persistent, long-horizon quantities, rather than the micro-structural effects of high-frequency trades. Investigating how price impact at different frequencies is connected lies beyond the scope of this paper, but represents an important direction for future research.

We emphasize that while the long-term price impact estimates are significantly larger than what is typically implied by the classic frictionless models, they are in fact consistent with estimates from the large microstructure literature: in fact, the high-frequency estimates reported in Brokmann et al. (2015), Bouchaud et al. (2018), and Frazzini, Israel, and Moskowitz (2018) are substantially larger than the bounds we obtain at quarterly and annual frequencies.

### 6.2 Differences in Price Impact in the Cross-Section of Stocks

In the following, we ask the question: Which stocks have higher price impact bounds? To this end, we regress $\mathcal{M}_{\text{EPS}}$ and $\tilde{\mathcal{M}}$ on various stock-specific characteristics such as size (market equity), systematic risk (market beta), momentum (cumulative past returns), book-to-market ratio, dividend to book equity ratio, profitability, and the illiquidity measure from Amihud (2002). Table 3 reports the results.

First, we find that $\mathcal{M}$ is significantly smaller for larger stocks. That is, a one standard deviation increase in stock size is associated with a 0.13 decline in price impact (t-statistic of 12). This aligns with the view that larger stocks are more liquid, possibly due to more precise and readily available information. Notably, however, this finding contrasts Haddad, Huebner, and Loualiche (2021) and Jiang, Zheng, and Vayanos (2025), who document that large stocks are *less* elastic than small stocks.

Second, stocks with higher market betas exhibit significantly larger price impacts, i.e., a one standard deviation increase in market beta raises the price impact by 0.1. This is consistent with standard CARA-normal intuition: stocks that contribute more to the risk of an arbitrage portfolio are more sensitive to demand shifts (Greenwood, 2005; Kozak, Nagel, and Santosh, 2018).

Third, stocks with stronger past cumulative returns (i.e., momentum stocks) have significantly larger price impacts. This finding aligns with the idea that momentum traders – with upward-sloping demand curves – continue to trade in the direction of the initial price movement, thereby reducing market liquidity and further amplifying price shifts.

Importantly, the documented patterns remain robust and in several cases strengthen when we

Table 3: **Heterogeneity in $\mathcal{M}$**

The table summarizes how $\mathcal{M}$ varies across different stocks. We regress $\mathcal{M}_{\text{EPS}}$ and the approximated price impact $\tilde{\mathcal{M}}$ on the stock-specific characteristics, log market equity, market beta, momentum, dividend to book equity, profitability, and Amihud illiquidity. When $\rho_{\text{EPS}}$ is missing for a given stock, we compute $\mathcal{M}_{\text{EPS}}$ using the cross-sectional average $\rho$ in our sample. Column (4) reports results for the restricted sample for which we can directly estimate $\rho$ from one-quarter-ahead EPS forecast revisions. Column (5) reports results for the approximated price impact $\tilde{\mathcal{M}}$, obtained by setting $\rho = 0.5$ for all stocks.

| | $\mathcal{M}_{\text{EPS}}$ | | | | $\tilde{\mathcal{M}}$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| log(ME) | -0.396***<br>(0.017) | -0.383***<br>(0.017) | -0.675***<br>(0.033) | -0.290***<br>(0.058) | -0.598***<br>(0.030) |
| $\beta$ | 0.121***<br>(0.010) | 0.159***<br>(0.011) | 0.148***<br>(0.013) | 0.166***<br>(0.021) | 0.134***<br>(0.012) |
| Cum. Ret. | 0.160***<br>(0.013) | 0.151***<br>(0.009) | 0.138***<br>(0.007) | 0.040***<br>(0.009) | 0.125***<br>(0.006) |
| BM | -0.111***<br>(0.013) | -0.110***<br>(0.012) | -0.127***<br>(0.012) | -0.063**<br>(0.020) | -0.113***<br>(0.011) |
| $\frac{\text{Dividend}}{\text{BE}}$ | 0.016<br>(0.009) | 0.023*<br>(0.009) | -0.028*<br>(0.011) | 0.016<br>(0.012) | -0.026*<br>(0.010) |
| Profit | -0.085***<br>(0.011) | -0.088***<br>(0.010) | -0.002<br>(0.011) | -0.037<br>(0.023) | 0.000<br>(0.010) |
| Amihud Illiquidity | 0.261***<br>(0.017) | 0.265***<br>(0.017) | 0.182***<br>(0.014) | 0.640***<br>(0.152) | 0.169***<br>(0.013) |
| Date FE | – | x | x | x | x |
| Stock FE | – | – | x | x | x |
| Observations | 288,920 | 288,920 | 288,920 | 61,743 | 288,920 |
| $R^2$ | 0.255 | 0.283 | 0.586 | 0.541 | 0.588 |
| $R^2_{\text{Within}}$ | – | 0.249 | 0.147 | 0.145 | 0.147 |

additionally control for stock fixed effects. Finally, our results also remain unchanged when we use our approximated price impact, $\tilde{\mathcal{M}} = \frac{\sigma_p}{\sigma_q}$, as an independent variable. This further corroborates the fact that our results appear not to be driven by the investor agreement parameter which is notoriously difficult to quantify.

### 6.3 Price Impact at Higher Levels of Aggregation

Our bounds are particularly helpful for investigating settings for which there is a lack of relevant and exogenous demand shifts, such as the aggregate stock market. Gabaix and Koijen (2021) find that the aggregate stock market is considerably more inelastic than individual stocks. Li and Lin (2022) find that price multipliers in the cross-section of individual stocks monotonically increase at higher levels of aggregation. Our price impact is informative about the role of demand shocks at different levels of aggregation as it relies only on two directly observable empirical moments: return volatility and portfolio turnover.

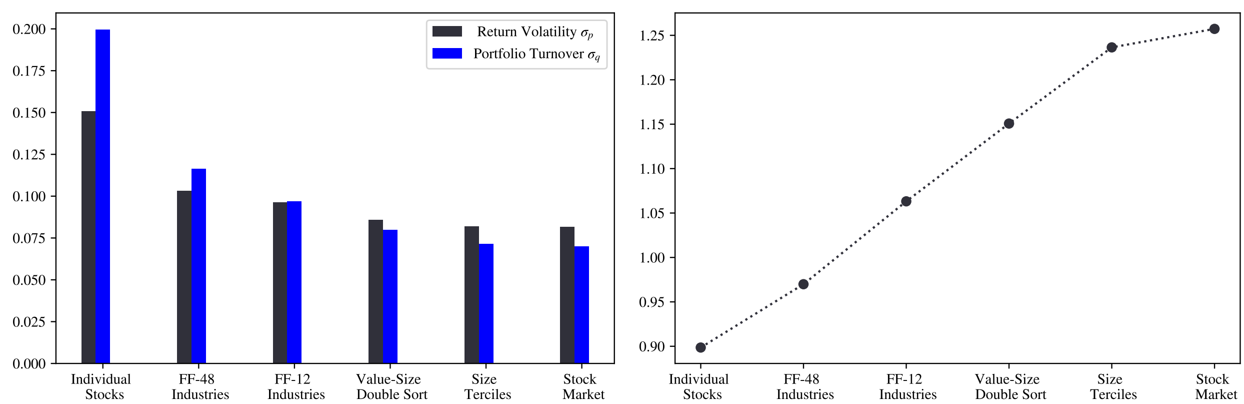
Specifically, we compute $\tilde{\mathcal{M}}$ using various aggregation levels. That is, we start from individual stocks and then successively aggregate to 49 Fama-French industry portfolios, 12 Fama-French industry portfolios, six portfolios double-sorted on size and book-to-market, three portfolios sorted on size, and, finally, one overall market portfolio. To avoid confusion with "portfolio turnover" – which refers specifically to trading activity from institutional holdings – we henceforth refer to these aggregation levels as groups, rather than portfolios. We first compute return volatility $\sigma_p(g)$ and portfolio turnover $\sigma_q(g)$ for each group. Let $g \subseteq N$ denote the subset of stocks belonging to a given group. Return volatility for group $g$ is then simply the rolling 5-year standard deviation of the value-weighted portfolio return. For example, for the aggregate stock market, $\sigma_p(g)$ is the standard deviation of the value-weighted return across all stocks. Portfolio turnover for group $g$ is given by

$$\text{Turnover}_t(g) = \frac{\sum_{i=1} \Delta |D_{i,t}(g)|}{D_{t-1}(g)}, \tag{31}$$

where $\Delta D_{i,t}(g) = \sum_{n \in g} \Delta Q_{i,t}(n) P_{t-1}(n)$ and $D_{t-1}(g) = \sum_{n \in g} \bar{Q}_{t-1}(n) P_{t-1}(n)$. The numerator measures the total dollar flow in and out of group $g$ between $t-1$ and $t$. The denominator measures the total dollar value of group $g$ as of $t-1$. For example, for the aggregate stock market, the denominator is given by the total stock market capitalization. As before, we then approximate $\sigma_q$ as the average of portfolio turnover, $\sigma_q(g) \approx \frac{\sqrt{\pi}}{2} \mathbb{E}[\text{Turnover}_t(g)]$, estimated from 5-year rolling windows.

Figure 7: **Bounds at different Levels of Aggregation**
Panel a) plots the volatility of returns $\sigma_p(g)$ and portfolio turnover $\sigma_q(g)$ at different levels of aggregation $g$ ranging from individual stocks to the aggregate stock market. Panel b) plots the bound-implied price impact for different levels of aggregation ranging from individual stocks, industries, characteristic portfolios and the aggregate stock market. For each level of aggregation, we plot $\frac{\sigma_p}{\sigma_q}$, which is the price impact implied by $\rho = 0.5$. We report value-weighted averages across assets within each aggregation level.

(a) Volatility and Turnover (b) Price Impact




Panel a) of Figure 7 plots our estimates of $\sigma_q(g)$ and $\sigma_p(g)$ at seven different levels of aggregation. At the individual stock level, portfolio turnover $\sigma_q$ is largest. As we aggregate stocks into progressively fewer buckets, $\sigma_q$ systematically declines. This pattern is intuitive: Investors' trades in a given stock within an aggregation level partly offset each other, which reduces portfolio turnover. At the same time, return volatility also declines with aggregation. As before, this is intuitive and expected from basic portfolio theory, where diversification reduces idiosyncratic risk. Importantly, however, what matters most for our price impact bounds is the relative speed at which the volatility of returns and portfolio turnover decline – ultimately, an empirical question. In the data, return volatility decreases at a lower pace. As a result, $\tilde{\mathcal{M}}$ rises with aggregation. Panel b) of Figure 7 shows that the average $\tilde{\mathcal{M}}$ increases monotonically with the level of aggregation – from 0.9 for individual stocks, to 1.05 for industry portfolios, and up to 1.3 for the aggregate market.

## 7 Conclusion

This paper reveals a fundamental tension between investor agreement and price impact: when return volatility is high while portfolio turnover is low, market participants cannot simultaneously disagree with each other and respond elastically to price changes. Otherwise we would observe much higher portfolio turnover. This implies that if one acknowledges that investors are not in perfect agreement with each other, one must also concede to considerable price impact, i.e., that markets are inelastic. In other words, given observable moments on quantities and prices, investor agreement and price impact cannot be modeled independently. Highly elastic investors (and thus low price impact) can only be reconciled with the data if investors exhibit a high degree of agreement with one another.

We formalize this trade-off through a model-free bound, $\mathcal{M} \geq \frac{\sigma_p}{\sigma_q} \times \sqrt{\frac{1}{\rho} - 1}$, that connects return volatility, portfolio turnover, and investor agreement to the price impact of persistent demand shifts. Our bounds inform the two competing views on the drivers of asset prices. The first view holds that trading volume is merely a byproduct of price formation and contains no incremental information beyond the representative investor's demand. The second view posits that trading volume is fundamental to understanding price movements, as shifts in quantities interact with a non-zero price impact.

Applied to U.S. equities, our bounds imply substantial price impacts for individual stocks, closely aligning with event study evidence from S&P 500 inclusions and mutual fund flows while traditional high-frequency liquidity measures fail to explain these price impacts. Our bounds vary systematically across assets – with larger stocks exhibiting lower price impacts and higher-beta stocks showing greater impacts – and increase substantially with portfolio aggregation. Our bound provides a diagnostic tool for structural models seeking to reconcile portfolio turnover and return volatilities, and a sanity check for empirical studies on investor disagreement and price impact.

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# Appendix A General Condition for Theorem 1

## A.1 Relaxed Assumption

We show that Theorem 1 holds under a weaker assumption that allows for cross-sectional dependence between elasticities and the data-generating process for demand shifts. To characterize this dependence without imposing structural assumptions, we define the following reduced-form object:

**Definition A.1.** *The demand beta of investor $i$, $\beta_i^u$, is the regression coefficient of their demand shift $u_{i,t}$ on the aggregate demand shift $u_{S,t}$:*

$$\beta_i^u \equiv \frac{\mathrm{Cov}(u_{i,t}, u_{S,t})}{\mathrm{Var}(u_{S,t})}$$

Demand beta $\beta_i^u$ captures how much investor $i$'s demand shift comoves with the aggregate demand shift. Recall $u_{S,t}$ is the average demand shift $\hat{\mathbb{E}}_S^{cs}[u_{i,t}]$. Hence, just as the size-weighted average of stock beta is 1, the average demand beta across investors is 1:

$$\hat{\mathbb{E}}_S^{cs}[\beta_i^u] = \frac{1}{\mathrm{Var}(u_{S,t})} \sum_i S_i \, \mathrm{Cov}(u_{i,t}, u_{S,t}) = 1.$$

To gain more intuition, consider a single-factor model for $u_{i,t}$ with $u_{i,t} = \lambda_i \eta_t + \varepsilon_{i,t}$, where $\eta_t \perp \varepsilon_{i,t} \perp \varepsilon_{j,t}$ for all $i \neq j$. Using the $S$ subscript to denote the size-weighted average, the demand beta of investor $i$ can be computed as:

$$\beta_i^u = \frac{\mathrm{Cov}(u_{i,t}, u_{S,t})}{\mathrm{Var}(u_{S,t})} = \frac{1}{\mathrm{Var}(u_{S,t})} \left(\lambda_i \lambda_S + S_i \sigma_{\varepsilon,i}^2\right).$$

An investor can have a high demand beta because their demand shifts are highly sensitive to common factors (high $\lambda_i$) that drive the aggregate demand shift, because they have large size (high $S_i$), or because they have more volatile idiosyncratic shocks (high $\sigma_{\varepsilon,i}$), making their demand shifts more represented in the aggregate.

We show that Theorem 1 holds under the following weaker assumption A.1:

**Assumption A.1.** *With $\beta_i^u$ defined as above, we have the following condition:*

$$\widehat{\mathrm{Var}}_S^{cs}\left(\frac{\zeta_i}{\zeta_S}\right) - 2\widehat{\mathrm{Cov}}_S^{cs}\left(\frac{\zeta_i}{\zeta_S}, \beta_i^u\right) \geq 0$$

Assumption A.1 relaxes the independence requirement in Assumption 1 by allowing for cross-sectional dependence between elasticities and the data-generating process for demand shifts, captured by the cross-sectional covariance between elasticity and demand beta, $\widehat{\text{Cov}}_S^{cs}\left(\frac{\zeta_i}{\zeta_S}, \beta_i^u\right)$. We first provide intuition for this assumption, then prove the theorem.

First, consider the case where $\widehat{\text{Cov}}_S^{cs}(\zeta_i, \beta_i^u) < 0$, where Assumption A.1 automatically holds. This negative covariance is the empirically natural case: liquidity providers (those with relatively high $\zeta_i$) absorb rather than amplify aggregate demand shifts (exhibiting relatively lower $\beta_i^u$).

Empirically, liquidity providers such as broker-dealers, hedge funds, and other arbitrageurs typically hold smaller positions, and their demand shifts often originate from liquidity management or arbitrage opportunities that are less correlated with aggregate demand shifts. In contrast, passive and benchmark-constrained investors exhibit low price elasticity by design, while their demand shifts – driven by end-investor flows and macroeconomic fundamentals – strongly comove with and substantially contribute to aggregate demand shifts.

As discussed in the main text, heterogeneity in elasticities increases flow volatility under independence, because investors' differential price responses create trading activity beyond that generated by disagreement alone. When $\widehat{\text{Cov}}_S^{cs}(\zeta_i, \beta_i^u) < 0$, this effect is amplified: investors' two trading motives – liquidity provision ($-\zeta_i p_t$) and demand shifts ($u_{i,t}$) – align with each other. Hence, the total flow volatility is higher than under independence, leading to a tighter bound on price impact.

In the opposite case where $\widehat{\text{Cov}}_S^{cs}(\zeta_i, \beta_i^u) > 0$, liquidity providers exhibit more procyclical demand shifts. Here, the two trading motives – liquidity provision ($-\zeta_i p_t$) and demand shifts ($u_{i,t}$) – counteract each other, dampening flow volatility. This scenario is less intuitive and can lead to pathological outcomes: when $\widehat{\text{Cov}}_S^{cs}(\zeta_i, \beta_i^u)$ becomes sufficiently large, investors with the highest demand may nonetheless sell, as their liquidity provision dominates their underlying demand shifts.[22]

Our Assumption A.1 accommodates moderate positive covariance, but requires that any such positive covariance be dominated by the dispersion in elasticities, $\widehat{\text{Var}}_S^{cs}(\frac{\zeta_i}{\zeta_S})$. We also note that when Assumption A.1 is violated under certain models, our bound can be modified accordingly to include the dispersion in elasticities and the dependence between elasticities and demand beta, as shown in the proof below.

[22] To be precise, we may have the empirical moment such that $\hat{\mathbb{E}}_S^{cs}[\text{Cov}(\Delta q_{i,t}, u_{i,t})] < 0$. Note that $\hat{\mathbb{E}}_S^{cs}[\text{Cov}(\Delta q_{i,t}, u_{i,t})] = \hat{\mathbb{E}}_S^{cs}[\sigma_i^2 - \frac{\zeta_i}{\zeta_S}\text{Cov}(u_{i,t}, u_{S,t})]$. Using $\hat{\mathbb{E}}_S^{cs}[\frac{\zeta_i}{\zeta_S}\text{Cov}(u_{i,t}, u_{S,t})] = \text{Var}(u_S)\big(1 + \widehat{\text{Cov}}_S^{cs}[\frac{\zeta_i}{\zeta_S}, \beta_i^u]\big)$ from the proof, we can show that $\hat{\mathbb{E}}_S^{cs}[\text{Cov}(\Delta q_{i,t}, u_{i,t})] < 0$ when $\widehat{\text{Cov}}_S^{cs}(\frac{\zeta_i}{\zeta_S}, \beta_i^u) > \frac{1}{\rho} - 1$.

## A.2 Proof under the Relaxed Assumption

*Proof of Theorem 1.* Given the demand curve equation (2) and price equation (4), we have

$$\Delta q_{i,t} = u_{i,t} - \frac{\zeta_i}{\zeta_S} u_{S,t},$$

Let $\sigma_i^2 \equiv \mathrm{Var}(u_{i,t})$ denote the variance of investor $i$'s demand shift. Using $\beta_i^u \equiv \frac{\mathrm{Cov}(u_{i,t}, u_{S,t})}{\mathrm{Var}(u_{S,t})}$, the variances of flows and price are:

$$\sigma_{q,i}^2 = \mathrm{Var}(\Delta q_{i,t}) = \sigma_i^2 - 2\frac{\zeta_i}{\zeta_S}\beta_i^u \mathrm{Var}(u_{S,t}) + \frac{\zeta_i^2}{\zeta_S^2}\mathrm{Var}(u_{S,t})$$

$$\sigma_p^2 = \mathrm{Var}(\Delta p_t) = \frac{1}{\zeta_S^2}\mathrm{Var}(u_{S,t})$$

The size-weighted average flow variance is:

$$\begin{aligned}
\sigma_q^2 &= \sum_i S_i \sigma_{q,i}^2 \\
&= \hat{\mathbb{E}}_S^{cs}\left[\sigma_i^2\right] - 2\,\mathrm{Var}(u_{S,t})\,\hat{\mathbb{E}}_S^{cs}\left[\tfrac{\zeta_i}{\zeta_S}\beta_i^u\right] + \left(\hat{\mathbb{E}}_S^{cs}\left[\tfrac{\zeta_i^2}{\zeta_S^2}\right]\right)\mathrm{Var}(u_{S,t}) \\
&= \hat{\mathbb{E}}_S^{cs}\left[\sigma_i^2\right] - 2\,\mathrm{Var}(u_{S,t})\left(\hat{\mathbb{E}}_S^{cs}\left[\tfrac{\zeta_i}{\zeta_S}\right]\hat{\mathbb{E}}_S^{cs}\left[\beta_i^u\right] + \widehat{\mathrm{Cov}}_S^{cs}\left[\tfrac{\zeta_i}{\zeta_S}, \beta_i^u\right]\right) + \left(\hat{\mathbb{E}}_S^{cs}\left[\tfrac{\zeta_i}{\zeta_S}\right]^2 + \widehat{\mathrm{Var}}_S^{cs}\left(\tfrac{\zeta_i}{\zeta_S}\right)\right)\mathrm{Var}(u_{S,t})
\end{aligned}$$

Notice that:

$$\hat{\mathbb{E}}_S^{cs}\left[\frac{\zeta_i}{\zeta_S}\right] = \frac{1}{\zeta_S}\sum_i S_i \zeta_i = 1$$

$$\hat{\mathbb{E}}_S^{cs}\left[\beta_i^u\right] = \frac{1}{\mathrm{Var}(u_{S,t})}\sum_i S_i \,\mathrm{Cov}\left(u_{i,t}, u_{S,t}\right) = 1$$

The expression can be simplified using $\hat{\mathbb{E}}_S^{cs}\left[\frac{\zeta_i}{\zeta_S}\right] = 1$ and $\hat{\mathbb{E}}_S^{cs}\left[\beta_i^u\right] = 1$ as:

$$\sigma_q^2 = \hat{\mathbb{E}}_S^{cs}\left[\sigma_i^2\right] - \mathrm{Var}\left(u_{S,t}\right) + \mathrm{Var}\left(u_{S,t}\right)\left(\widehat{\mathrm{Var}}_S^{cs}\left(\tfrac{\zeta_i}{\zeta_S}\right) - 2\widehat{\mathrm{Cov}}_S^{cs}\left[\tfrac{\zeta_i}{\zeta_S}, \beta_i^u\right]\right)$$

Factoring out $\mathrm{Var}\left(u_{S,t}\right)$ and using the definition $\rho = \frac{\mathrm{Var}(u_{S,t})}{\hat{\mathbb{E}}_S^{cs}[\sigma_i^2]}$ from the main text, we have:

$$\sigma_q^2 = \mathrm{Var}\left(u_{S,t}\right)\left(\frac{1}{\rho} - 1 + \widehat{\mathrm{Var}}_S^{cs}\left(\tfrac{\zeta_i}{\zeta_S}\right) - 2\widehat{\mathrm{Cov}}_S^{cs}\left[\tfrac{\zeta_i}{\zeta_S}, \beta_i^u\right]\right)$$

The ratio of $\sigma_q^2$ to $\sigma_p^2$ is given as:

$$\frac{\sigma_q^2}{\sigma_p^2} = \zeta_S^2 \left( \frac{1}{\rho} - 1 + \widehat{\text{Var}}_S^{cs}\left(\frac{\zeta_i}{\zeta_S}\right) - 2\widehat{\text{Cov}}_S^{cs}\left[\frac{\zeta_i}{\zeta_S}, \beta_i^u\right] \right).$$

Under Assumption A.1, the last two terms, $\widehat{\text{Var}}_S^{cs}\left(\frac{\zeta_i}{\zeta_S}\right)$ and $-2\widehat{\text{Cov}}_S^{cs}\left(\frac{\zeta_i}{\zeta_S}, \beta_i^u\right)$, are nonnegative in sum, and hence:

$$\frac{\sigma_q^2}{\sigma_p^2} \geq \zeta_S^2 \left( \frac{1}{\rho} - 1 \right).$$

Taking square roots (noting $\rho \in [0, 1]$ so the square root is well-defined) and using $\mathcal{M} = \frac{1}{\zeta_S}$, we obtain the bound:

$$\mathcal{M} \geq \frac{\sigma_p}{\sigma_q} \times \sqrt{\frac{1}{\rho} - 1}$$

□

# Appendix B Microfoundations

In this section, we derive the linear demand curve from canonical models to help readers interpret this representation. To provide the clearest intuition, we keep the model intentionally stylized. In reality, investors face considerably more complex portfolio choice problems involving multiple mechanisms. We therefore do not seek to establish a precise mapping between our reduced-form quantities – price impact and investor heterogeneity – and the structural parameters underlying these models.

We start with demand curve representations of portfolio choice under CRRA utility with rational expectations in Section B.1. We then extend the analysis to a learning-from-price model in Section B.2.

## B.1 CRRA Utility

Consider the portfolio choice problem of an investor with CRRA utility and rational expectations in a two-period model. Investors are endowed with $E_i$ shares of stocks. With log-normal returns and the standard small-risk approximation (Campbell and Viceira, 2002), the utility maximization gives the standard portfolio choice

$$\frac{PQ_i}{W_i} = \frac{\mathbb{E}\left[\frac{D}{P}\right] - R_f}{\gamma_i \sigma_R^2},$$

where $W_i = E_i P$ is the investor's wealth, $\gamma_i$ is the risk aversion, $R_f$ is the total risk-free rate, and $\sigma_R$ is the return volatility.

We perturb the portfolio-choice problem around a given equilibrium with first-order log-linearization:

$$\Delta q_i \approx -\bar{\delta}\Delta p + \underbrace{\Delta e_i + \bar{\delta}\mathbb{E}\left[\Delta d\right] - \Delta \log \gamma_i - \Delta \log \sigma_R^2}_{u_i} \tag{B.1}$$

Here $\Delta q_i$ and $\Delta p$ denote log deviations of holdings and price, respectively (i.e., changes in $\log Q_i$ and $\log P$). Overbars denote equilibrium values, and $\bar{\delta} \equiv \frac{\overline{\mathbb{E}[\frac{D}{P}]}}{\overline{\mathbb{E}[\frac{D}{P}]} - \overline{R_f}}$ is the ratio of expected (gross) return to the expected excess return. The demand shift $u_i$ includes several components: $\Delta e_i$ (the log deviation of endowment), changes in expected dividends $\mathbb{E}[\Delta d]$, and changes in risk aversion and volatility.

The standard CRRA model under rational expectations features a homogeneous elasticity: the demand elasticity $\bar{\delta}$ is determined by the risk-free rate and the expected return, which in equilibrium is further pinned down by the return volatility and average risk aversion. It is well-known in the literature that the standard CRRA utility generates a very high demand elasticity. As a numerical example, suppose the (gross) expected return from the stock is 1.08, and the (gross) risk-free return is 1.02; the implied elasticity is around 18. According to our price impact bound, this requires a counterfactually high investor agreement ($\rho > 0.99$) to be consistent with the data.

The demand shift $u_i$ in the CRRA model comes from different sources. Some are aggregate factors, such as the expected dividend growth and the return volatility, while others have idiosyncratic components, like changes in risk aversion and the initial endowment. Our agreement measure $\rho$ captures the common variation in all these factors.

### B.2 Learning-From-Price Model à la Hellwig (1980)

We extend the CRRA model to incorporate learning-from-price, adapting the framework from Hellwig (1980).

To isolate the learning-from-price mechanism, we consider a simplified setting. Demand shifts arise solely from heterogeneous expectations about dividend changes:

$$\Delta q_i = -\bar{\delta}\Delta p + \bar{\delta}\mathbb{E}_i\left[\Delta d\right] \tag{B.2}$$

The crucial assumption is that investors form expectations about dividend changes using both a private signal $s_i$ and information extracted from the equilibrium price. We specify the information structure in detail later. Here, we postulate that expected dividend changes are formed as a linear combination:

$$\mathbb{E}_i [\Delta d] = \alpha_{i,s} s_i + \alpha_{i,p} \Delta p \tag{B.3}$$

where $\alpha_{i,s} > 0$ and $\alpha_{i,p} > 0$ are equilibrium coefficients that reflect how much weight investors place on their private signals versus price information.

Substituting (B.3) into (B.2) gives us the demand curve with learning-from-price:

$$\begin{aligned} \Delta q_i &= -\bar{\delta} \Delta p + \bar{\delta} \left( \alpha_{i,s} s_i + \alpha_{i,p} \Delta p \right) \\ &= -\underbrace{\bar{\delta} \left( 1 - \alpha_{i,p} \right)}_{\zeta_i} \Delta p + \underbrace{\bar{\delta} \alpha_{i,s} s_i}_{u_i} \end{aligned} \tag{B.4}$$

The key insight is that learning from prices makes demand less elastic: the elasticity $\zeta_i = \bar{\delta}(1 - \alpha_{i,p})$ is smaller than the elasticity $\bar{\delta}$ under rational expectations. When investors observe a price increase, they partly interpret it as conveying positive information about fundamentals, leading them to increase rather than decrease their demand.

This mechanism amplifies price impact. When an uninformed demand shock enters the market, investors cannot distinguish it from informed trading. They cautiously interpret the resulting price movement as reflecting positive private information and are therefore more reluctant to trade against it. Consequently, each unit of demand shock requires a larger price adjustment to clear the market.

Recall that investor agreement $\rho$ concerns the correlation of demand shifts $u_i$—changes in portfolio choice holding price fixed. In this learning-from-price context, agreement reflects the correlation in investors' private signals and their responses, $\alpha_{i,s} s_i$. Crucially, agreement is not about the correlation in expected dividend changes $\mathbb{E}_i [\Delta d]$, which incorporate information from equilibrium prices. It is possible that investors can ex-ante disagree but ex-post agree if they choose to lean strongly on the price. However, this would imply investors are very inelastic to price and hence the price impact would be high, consistent with our bound.

To interpret the demand curve in the main text, Equation (B.4) is sufficient. For completeness, below we provide a full characterization of the equilibrium to pin down the coefficients $\alpha_s$ and $\alpha_p$.

**Equilibrium Characterization** To fully characterize the equilibrium, we need to determine $\alpha_s$ and $\alpha_p$. We consider the symmetric case for analytical tractability. Consider a market with $N$ agents of respective sizes $S_i$ (where $\sum_i S_i = 1$); we will eventually take $N$ to infinity for analytical tractability. The market also contains noise traders who submit random orders $u_n$; these prevent prices from being perfectly revealing.

Market clearing requires:

$$\sum_i S_i \Delta q_i = 0$$

From the demand equation (B.4), market clearing implies:

$$\begin{aligned} 0 &= -\zeta \Delta p + \bar{\delta}\alpha_s \sum_i S_i s_i + u_n \\ \Rightarrow \quad \Delta p &= \frac{\bar{\delta}\alpha_s s_S + u_n}{\zeta} \end{aligned} \tag{B.5}$$

where $s_S \equiv \sum_i S_i s_i$ is the size-weighted average signal. This can be rewritten as:

$$\Delta p = \frac{\alpha_s}{1-\alpha_p} \left( s_S + \underbrace{\frac{u_n}{\bar{\delta}\alpha_s}}_{\equiv s_N} \right)$$

where $s_N$ represents the effective "noise signal" from noise trading.

**Information Structure and Signal Extraction** We assume the fundamental follows:

$$D = \bar{D} \exp\left( \Delta d - \frac{1}{2}\sigma^2_{\Delta d} \right)$$

where $\Delta d \sim \mathcal{N}(0, \sigma^2_{\Delta d})$.

Each investor receives a private signal $s_i \sim \mathcal{N}(0, \sigma_s^2)$ with the following correlation structure:

$$\text{Cov}(s_i, s_j) = \rho\sigma_s^2 \quad \text{for } i \neq j \tag{B.6}$$

$$\text{Cov}(s_i, \Delta d) = \beta\sigma_s^2 \tag{B.7}$$

The coefficient $\rho$ controls the correlation of signals across investors, while the coefficient $\beta$ captures how informative each signal is for the true fundamental.

In the limit as $N \to \infty$, the conditional expectation of $\Delta d$ given signals $s_i$ and the aggregate signal

$s_S + s_N$ (a linear function of the price) is:

$$\mathbb{E}\left[\Delta d \mid s_i, s_S + s_N\right] = \frac{\beta\sigma_N^2}{\sigma_N^2 + \sigma_s^2\rho(1-\rho)}\, s_i + \frac{\beta\sigma_s^2(1-\rho)}{\sigma_N^2 + \sigma_s^2\rho(1-\rho)}\,(s_S + s_N) \tag{B.8}$$

where $\sigma_N^2$ is the variance of the noise signal $s_N$. The derivation is provided at the end of this section.

Using the price equation, we can express this conditional expectation in terms of $s_i$ and $\Delta p$:

$$\mathbb{E}\left[\Delta d \mid s_i, \Delta p\right] = \alpha_s s_i + \alpha_p \Delta p$$

Matching coefficients, we obtain:

$$\alpha_s = \frac{\beta\sigma_N^2}{\sigma_N^2 + \sigma_s^2\rho(1-\rho)} \tag{B.9}$$

$$\alpha_p = \frac{\sigma_s^2(1-\rho)}{\sigma_N^2 + \sigma_s^2(1-\rho)} \tag{B.10}$$

Substituting back into the demand equation:

$$\Delta q_i = \underbrace{\bar{\delta}\frac{\beta\sigma_N^2}{\sigma_N^2 + \sigma_s^2\rho(1-\rho)}}_{u_i}\, s_i - \underbrace{\bar{\delta}\frac{\sigma_N^2}{\sigma_N^2 + \sigma_s^2(1-\rho)}}_{\zeta}\,\Delta p$$

The final elasticity expression reveals the trade-off inherent in learning from prices. On one hand, when private signals are less correlated across investors (low $\rho$), more new information can be extracted from the price, making the market more inelastic. On the other hand, when noise trader flows are larger (high $\sigma_N^2$), the price becomes a less precise signal, making the market more elastic.

**Derivation of the conditional expectation formula**

*Proof.* The signal covariance matrix is given as (treating each $i$ as infinitesimally small):

$$\Sigma_s = \text{Var}\left(\begin{bmatrix} s_i \\ s_S + s_N \end{bmatrix}\right) = \begin{bmatrix} \sigma_s^2 & \rho\sigma_s^2 \\ \rho\sigma_s^2 & \rho\sigma_s^2 + \sigma_N^2 \end{bmatrix}$$

To compute the (2,2) entry, notice that:

$$\begin{aligned}\text{Var}(s_S) = \text{Var}\left(\sum_i S_i s_i\right) &= \sigma_s^2\left(\sum_i S_i^2 + \sum_{i\neq j} S_i S_j \rho\right)\\ &= \sigma_s^2\left((1-\rho)\sum_i S_i^2 + \rho\sum_i\sum_j S_i S_j\right)\\ &= \sigma_s^2\left(\rho + (1-\rho)\mathcal{H}\right)\end{aligned}$$

where $\mathcal{H} = \sum_i S_i^2$. Taking the limit as $N \to \infty$, we have $\mathcal{H} \to 0$, so $\text{Var}(s_S) = \rho\sigma_s^2$.

The covariance between signals and $\Delta d$ is:

$$\begin{aligned}\text{Cov}(\Delta d, s_i) &= \beta\sigma_s^2\\ \text{Cov}(\Delta d, s_S + s_N) &= \beta\sigma_s^2\end{aligned}$$

Thus,

$$\Sigma_{s,\Delta d} = \begin{bmatrix}\beta\sigma_s^2\\ \beta\sigma_s^2\end{bmatrix}.$$

The conditional expectation is given by

$$\Sigma_{s,\Delta d}^T \Sigma_s^{-1}\begin{bmatrix}s_i\\ s_S + s_N\end{bmatrix}.$$

Computing this yields B.8. □

# Appendix C Price Impact Bound with Substitution across Assets

When strong substitution exists across assets, the interpretation of the price impact bound requires extra care. To illustrate the point, in this section, we consider a classic arbitrage example: a single-name ETF $e$ and its underlying stock $s$.

We start with the single-price representation of the demand system, as derived in the main text:

$$
\begin{aligned}
\Delta q_{i,t}(s) &= -\underbrace{\zeta(s)\ (1-\mathcal{Q}_{s\leftarrow e}\,\mathcal{Q}_{e\leftarrow s})}_{\tilde{\zeta}(s)=1/\mathcal{M}(s)}\,\Delta p_t(s)\ +\ \underbrace{\mathcal{Q}_{s\leftarrow e}\,u_{S,t}(e)\ +\ u_{i,t}(s)}_{\tilde{u}_{i,t}(s)} \\
\Delta q_{i,t}(e) &= -\underbrace{\zeta(e)\ (1-\mathcal{Q}_{e\leftarrow s}\,\mathcal{Q}_{s\leftarrow e})}_{\tilde{\zeta}(e)=1/\mathcal{M}(e)}\,\Delta p_t(e)\ +\ \underbrace{\mathcal{Q}_{e\leftarrow s}\,u_{S,t}(s)\ +\ u_{i,t}(e)}_{\tilde{u}_{i,t}(e)}
\end{aligned}
\tag{C.1}
$$

To illustrate potential issues arising from strong cross-asset substitution, we consider the following numerical example.

**A numerical example** Consider an asymmetric market between the ETF and stock: the ETF is ten times smaller than the stock and less actively traded (small $\sigma_q(e)$), but the no-arbitrage condition ensures the ETF price closely tracks the stock.

Numerically, let the price volatilities be $\sigma_p(s) = \sigma_p(e) = 0.1$ with near-perfect correlation, $\text{corr}(\Delta p_s, \Delta p_e) \approx 1.00$. Let the flow volatility be $\sigma_q(s) = 0.1$ for the stock, and $\sigma_q(e) = 0.01$ for the ETF. For convenience, assume investor agreement of $\rho(s) = \rho(e) = 0.5$, so $\sqrt{\frac{1}{\rho} - 1} = 1$. This gives aggregate demand shift volatilities $\sigma_{uS}(s) = 0.1$ and $\sigma_{uS}(e) = 0.01$, respectively.[23] For simplicity, assume demand shifts are uncorrelated across assets – introducing correlation does not change the main point.

The moments we specified above can be induced by the following demand elasticity matrix:

$$
\Gamma = \begin{pmatrix} -\zeta(s) = -100.3 & \zeta(s,e) = 99.7 \\ \zeta(e,s) = 998.5 & -\zeta(e) = -1002.5 \end{pmatrix}
$$

Under this demand system, we have the following reduced-form moments:

$$
\mathcal{M}(s) = 1, \quad \mathcal{M}(e) \approx 0.1, \quad \mathcal{Q}_{s\leftarrow e} \approx 0.099, \quad \mathcal{Q}_{e\leftarrow s} \approx 9.95, \quad \mathcal{A} = 1 - \mathcal{Q}_{s\leftarrow e}\,\mathcal{Q}_{e\leftarrow s} \approx 0.01
$$

We choose the demand elasticity matrix $\Gamma$ to be asymmetric, reflecting the size difference between markets: the stock market is ten times larger than the ETF market. Consequently, investor demand for the stock responds less to ETF price changes than vice versa. In terms of demand pass-throughs, a 1% demand shift to the ETF translates to approximately 0.1% effective demand shift to the stock, while a 1% demand shift to the stock generates an effective 10% demand shift to the ETF. This asymmetry illustrates when our bound remains appropriate despite strong substitution, and when it becomes less

[23]Notice that by replacing the endogenous prices from the demand equation we again have $\Delta q_{i,t}(\cdot) = u_{i,t}(\cdot) - u_{S,t}(\cdot)$, hence $\sigma_q(\cdot) = \sigma_{uS}(\cdot)\sqrt{\frac{1}{\rho(\cdot)} - 1}$.

informative.

In this context, we interpret the key objects in the bound: the price impact $\mathcal{M}(s)$ and the investor agreement $\rho(s)$.

**Interpreting price impact $\mathcal{M}$.** As discussed in the main text, our bound correctly recovers the price impact $\mathcal{M}(\cdot)$. However, under strong substitution, price impact differs substantially from the reciprocal of price elasticity $\zeta(\cdot)$. In this example, the price impact for the stock is approximately 1, while the own-price elasticity is around 100.

Understanding this difference requires recognizing that "elasticity" is a partial-equilibrium concept holding all other prices constant, while price impact incorporates general-equilibrium effects. "Elasticity" captures demand response to stock price changes while *holding the ETF price constant.* Given the close arbitrage relationship, investors are highly sensitive to price discrepancies between the ETF and stock, leading to aggressive arbitrage trading. Conversely, price impact captures how stock prices respond to demand shocks *accounting for general-equilibrium effects*: the demand shift also moves ETF prices, which recursively affects stock demand. The amplification factor $\mathcal{A} := (1 - \mathcal{Q}_{n \leftarrow n'} \mathcal{Q}_{n' \leftarrow n})$ illustrates this feedback loop: a 1% stock demand shift generates a $\mathcal{Q}_{n' \leftarrow n} \approx 9.95\%$ effective demand shift to the ETF, which feeds back to the stock as $\mathcal{Q}_{n \leftarrow n'} \mathcal{Q}_{n' \leftarrow n} \approx 0.99\%$.

Under very strong substitution, our bound identifies the price impact but becomes uninformative about the underlying elasticity. Which parameter matters depends on the research question. For understanding market-wide price responses, the reduced-form price impact is often the key quantity of interest – the reciprocal of the price impact can be loosely interpreted as the price elasticity of the combined stock-ETF system. However, if the goal is estimating arbitrage strength between the stock and ETFs, our bound is ill-suited. Such applications require cross-sectional identification strategies that compare differential asset responses to shocks, as developed in Chaudhary, Fu, and Li (2023) and Haddad, He, et al. (2025).

**Interpreting investor agreement $\rho$.** With multiple assets, the effective demand shift for one asset $\tilde{u}_{i,t}(s)$ depends not only on $u_{i,t}(s)$ but also on the aggregate demand shift to its substitute $u_{S,t}(e)$. This substitute term enters because it moves substitute prices, effectively shifting the demand curve for asset $s$ through substitution effects. The coefficient for $u_{S,t}(e)$ is $\mathcal{Q}_{s \leftarrow e}$, justifying our interpretation as demand pass-through: it measures the effective demand shift to asset $s$ from a unit aggregate demand shift to $e$.

Investor agreement $\rho$ measures the comovement of the total demand shifts $\tilde{u}_{i,t}(s)$ across investors, which in this case has an additional common factor: the aggregate demand shifts to the substitute $u_{S,t}(e)$.

Under strong substitution, high investor agreement $\rho$ can emerge even when investors strongly disagree on asset-specific fundamentals. Consider the ETF in our example: even though investors may have heterogeneous ETF demand shifts $u_{i,t}(e)$, they all recognize the close arbitrage relationship between the ETF and underlying stock. Since the underlying stock is a much larger market and much more actively traded than the ETF, stock fundamental shifts passed to the ETF $\mathcal{Q}_{e\leftarrow s}u_{S,t}(s)$ dominate ETF-specific demand shifts $u_{i,t}(e)$. In our numerical example, $\text{Var}(\mathcal{Q}_{e\leftarrow s}u_{S,t}(s)) \approx 1$ while $\text{Var}(u_{S,t}(e)) \approx 0.0001$.

As $u_{S,t}(s)$ is reflected in the stock price and shared across investors, this creates high agreement $\rho$. If an econometrician naively applies the bound to the ETF using $\rho = 0.5$ for asset-specific demand shifts, they would recover a counterfactually high price impact $\mathcal{M}(e) \approx \frac{0.1}{0.01}\sqrt{\frac{1}{0.5} - 1} \approx 10$. This overestimate occurs because the true agreement incorporating substitution effects is close to 0.9999. For $\rho$ close to one, the bound is highly nonlinear and less informative.

Having close substitutes does not automatically invalidate the bound – it depends on the magnitude of demand shifts passed from substitutes. In our example, the bound remains informative for the stock: given the relative market size and activity, demand shifts originating from the ETF market are negligible ($\mathcal{Q}_{s\leftarrow e} \approx 0.1$ and $\sigma_{uS}(e) = 0.01$) compared to stock-specific demand shifts $\sigma_{uS}(s) \approx 0.1$. In this case, the investor agreement $\rho$ is still mostly about the stock fundamentals. Using our bound, one can recover the price impact for the stock as $\mathcal{M}(s) = \frac{0.1}{0.1}\sqrt{\frac{1}{0.5} - 1} \approx 1$, close to the true value.

# Appendix D Data Construction Details

## D.1 Flow Measures

Quarterly trades $\Delta Q_{i,t}(n)$ and changes in shares outstanding $\Delta\bar{Q}_t(n) = \bar{Q}_t(n) - \bar{Q}_{t-1}(n)$ are adjusted for stock splits in quarter $t$. We construct trades by the residual investor as $\Delta Q_{0,t}(n) = \Delta\bar{Q}_t(n) - \sum_{i=1}^{I}\Delta Q_{i,t}(n)$. All results in the paper are robust to omitting the residual sector and constructing $\bar{Q}_t(n)$ (and the corresponding size weights) as the sum of institutional shares held. However, we prefer the construction of the residual sector as this effectively accounts for trades by the institutional sector as a whole, which would otherwise be omitted. Furthermore, scaling by institutional shares held leads to some large outliers for smaller stocks that are held by very few institutions. Quarterly trades in percent are denoted by $q_{i,t}(n) = \frac{\Delta Q_{i,t}(n)}{Q_{i,t-1}(n)}$. To reduce the effect of outliers, we also use the Davis-Haltiwanger growth rate (Davis and Haltiwanger, 1992), following Gabaix and Koijen (2021) $q_{i,t}(n) = \frac{2(Q_{i,t}(n)-Q_{i,t-1}(n))}{Q_{i,t}(n)+Q_{i,t-1}(n)}$. The results are robust to either definition. When using portfolio turnover as the $\mathcal{L}_1$ approximation of flow volatility (the size-weighted standard deviation of $q_{i,t}(n)$), there is no need to express trades in percent, as portfolio turnover sums raw trades $\Delta Q_{i,t}(n)$ relative to supply. This makes portfolio turnover a more robust estimator, less sensitive to outliers, and the treatment of extensive versus intensive margin trades.

### D.2 Portfolio Turnover at the Fund Level

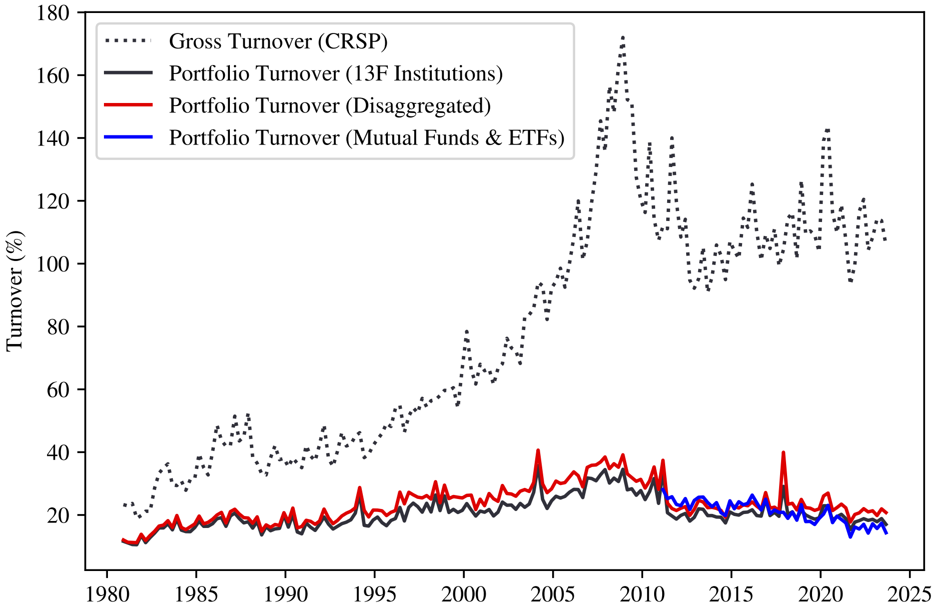
In the main text, we compute portfolio turnover at the 13F institution level to ensure comprehensive coverage. However, for asset managers with multiple subsidiary funds, institution-level portfolio turnover excludes intrafamily transactions, which may potentially explain why portfolio turnover is smaller than gross turnover. This section uses disaggregated mutual fund holdings data to demonstrate that netting effects from within-institution aggregation are negligible.

We disaggregate fund families in the 13F institutional holdings data (S34 file) using Thomson Reuters mutual fund holdings data (S12 file). Using the S12-S34 link table, we match mutual fund holdings to their corresponding asset managers in the 13F data. For asset managers whose total holdings exceed the sum of their subsidiary fund holdings, we construct a residual entity representing the difference between institutional and mutual fund holdings. We retain institutions in the 13F data that are not matched to any mutual fund. We then compute portfolio turnover from this merged dataset using the same methodology as in the main text.

As an additional validation, we construct fund-level portfolio turnover using an alternative source: the CRSP Survivor-Bias-Free US Mutual Fund Database, which provides comprehensive coverage of mutual funds and ETFs but excludes other investor types. Since these funds account for a smaller share of market ownership than the broader 13F universe, we normalize portfolio turnover within the dataset – dividing net trading activity by the total shares held by all CRSP funds, rather than by shares outstanding. Normalizing by shares outstanding would yield much smaller portfolio turnover and render it noncomparable to that based on 13F data.

Figure D.1 compares portfolio turnover measures computed using these two approaches with our baseline institution-level measures. The red line shows the portfolio turnover computed from the disaggregated 13F data using S12 mutual fund holdings files. The blue line presents portfolio turnover computed from the CRSP Survivor-Bias-Free US Mutual Fund Database. Despite being computed from different data sources and aggregation levels, the baseline institutional portfolio turnover is very close to the fund-level measures, confirming that netting effects from within-institution aggregation are negligible.

Figure D.1: **Portfolio Turnover at the Fund Level**
The figure compares portfolio turnover measures at the 13F institutional level with portfolio turnover computed at the fund level. *Portfolio Turnover* (in black) shows the baseline portfolio turnover computed from 13F institutional holdings data. *Portfolio Turnover Disaggregated* (in red) presents portfolio turnover computed from 13F data disaggregated using Thomson Reuters S12 mutual fund holdings files. *Portfolio Turnover Mutual Fund & ETFs* (in blue) presents portfolio turnover computed from the CRSP Survivor-Bias-Free US Mutual Fund Database, normalized within the dataset.




## D.3 Measuring Investor Agreement from I/B/E/S

We measure investor agreement using analyst forecast data from I/B/E/S, leveraging the idea that the cross-sectional distribution of analyst beliefs serves as a proxy for the cross-sectional distribution of investor demand. This section details the sample construction and methodology for estimating the agreement parameter $\rho$.

### D.3.1 Data Sources and Sample Selection

We obtain analyst earnings forecasts from the I/B/E/S Detail History database (`ibes.det_epsus`). We only use S&P 500 constituent firms to ensure sufficient number of forecasts. We then link I/B/E/S tickers to CRSP identifiers through a multi-step process: first matching I/B/E/S tickers to Compustat's `gvkey` using the security linking table (`comp.security`), then connecting `gvkey` to CRSP's `permno` through the CCM linking table using link types `LU` and `LC`. Finally, we filter for forecasts made while firms were S&P 500 constituents using historical index membership data.

We focus on two types of forecasts:

- **Quarterly Earnings-per-Share (EPS) forecasts** (FPI codes 6, 7, 8, 9): Representing 1- through 4-quarter ahead EPS forecasts;
- **Long-term growth (LTG) forecasts** (FPI code 0): Representing long-term earnings growth rates.

### D.3.2 Construction of Forecast Updates

We identify forecasters at the institution level (`estimator`, brokerage house or sell-side institution), to be consistent with the holdings data which is also at the 13F institution level.

For each forecaster-firm pair, we track how forecasts evolve over time:

**EPS Forecast Updates:** For quarterly EPS forecasts, we track how forecasters update their forecasts for a specific earnings announcement as it approaches. Each forecast target is uniquely identified by the firm and fiscal period end date (`fpedats`), with the actual earnings released on `anndats_act`. We define the forecast horizon as the number of days between when a forecast is made (`anndats`) and when actual earnings are released (`anndats_act`), converted to quarters by dividing by 90. We retain forecasts made within 400 days of the actual release and round horizons to the nearest quarter with a 30-day tolerance window. When multiple forecasts exist for the same forecaster-target-horizon combination, we select the earliest forecast.

Denote the log of forecasted EPS by forecaster $i$ at time $t$ for firm $n$ and horizon $h$ as $f_{i,t}^{h}(n)$. Updates are then calculated as percentage changes between consecutive horizons for the same target:

$$\Delta f_{i,t}^{h}(n) = f_{i,t}^{h}(n) - f_{i,t-1}^{h+1}(n)$$

By construction, $f_{i,t}^{h}(n)$ is around 90 days later than $f_{i,t-1}^{h+1}(n)$, matching the frequency of holdings data.

**LTG Forecast Updates:** Long-term growth forecasts differ from EPS forecasts as they lack a specific target date and thus no natural horizon measure. For these forecasts, we track quarter-to-quarter changes by assigning each forecast to a quarter based on its announcement date (`anndats`). To avoid partial quarter effects, forecasts made 45 or more days into a quarter are assigned to the following quarter. For each forecaster-firm-quarter combination, we retain only one forecast (the earliest if multiple exist). Updates are then calculated as simple differences (not percentages) between consecutive quarterly LTG forecasts:

$$\Delta f_{i,t}^{LTG}(n) = f_{i,t}^{LTG}(n) - f_{i,t-1}^{LTG}(n)$$

where $f_{i,t}^{LTG}(n)$ is the long-term growth forecast by forecaster $i$ in quarter $t$ for firm $n$.

### D.3.3 Estimation of Agreement $\rho$

Following our theoretical framework, we estimate forecaster agreement $\rho(n)$ as the adjusted $R^2$ from regressing individual forecast updates on time fixed effects. Specifically, for each firm $n$ and forecast type (EPS at horizon $h$ or LTG), we then estimate:

$$\Delta \hat{f}_{i,t}^{h}(n) = \overline{\Delta f_t^h(n)} + \epsilon_{i,t}^h(n) \quad \text{for each } h \in \{1, 2, 3, LTG\}$$

where $\Delta \hat{f}_{i,t}^{h}(n) = \Delta f_{i,t}^{h}(n) - \overline{\Delta f_i^h(n)}$ are the demeaned forecast updates within each forecaster-horizon-firm combination, and $\overline{\Delta f_t^h(n)}$ are time fixed effects. The adjusted $R^2$ from this regression captures the proportion of forecast update variation explained by common time effects, serving as our measure of agreement $\rho_{EPS}^h(n)$.

We use adjusted $R^2$ as opposed to the original $R^2$, as the latter can incur a large bias when the number of forecasters is small: When there are only $N$ forecasters, the expected raw $R^2$ will be around $\frac{1}{N}$ even with completely independent forecasts (hence the population $R^2$ is 0), while the adjusted $R^2$ have an expectation of 0 in this case. However, the adjusted $R^2$ can be negative in the sample. In these rare cases (mostly occur in the LTG forecasts when number of forecasters is small), we truncate the adjusted $R^2$ at 0.

To further reduce noises due to unbalanced panels, we apply the following filters before estimating $\rho_{EPS}^h(n)$: For each firm-horizon pair in quarterly EPS forecasts, we drop forecasters with less than 5 periods of forecast updates, and drop periods with less than 5 forecasters per firm-horizon combination. We repeat this filter iteratively until no more forecasters or periods can be dropped. The LTG forecasts are more sparse, hence we lower the threshold for the number of periods of forecast updates per forecaster-firm-quarter combination and the number of forecasters per firm-quarter combination to 4 and 3, respectively. Table D.1 reports the average characteristics of the final sample.

Table D.1: I/B/E/S Average Number of Forecasters and Updates
The table reports average characteristics of the I/B/E/S forecast sample used to estimate investor homogeneity. "N Periods" refers to the average number of time periods with forecasts per firm-horizon pair. "Number of Forecasters" is the average number of unique estimators covering each firm-horizon pair. "Number of Updates per Period" is the average number of forecast updates per firm-period. "Number of Updates" is the total average number of forecast updates per firm. 1Q-3Q refer to one-quarter through three-quarters ahead EPS forecasts, and LTG refers to long-term growth forecasts.

| Horizon | Number of Periods | Number of Forecasters | Number of Updates per Period | Number of Updates |
|---|---|---|---|---|
| 1Q | 44.2 | 26.0 | 11.5 | 510.2 |
| 2Q | 41.3 | 25.0 | 10.9 | 452.4 |
| 3Q | 37.6 | 22.6 | 10.1 | 379.8 |
| LTG | 16.5 | 5.2 | 3.5 | 57.7 |

### D.4 Estimate Agreement $\rho(n)$ Structurally

We use a workhorse structural model, designed to jointly match portfolio holdings and prices, to infer stock-level $\rho$. To this end, we take Koijen and Yogo, 2019, and estimate stock-level agreement $\rho$ from the investor-level demand shifts implied by their model. We acknowledge that using the $\rho$ computed in Koijen and Yogo, 2019 for our bounds requires assuming that elasticities estimated from portfolio holdings in levels correspond to quarterly elasticities. However, Beck, 2022 shows that such level-based estimates instead capture long-run elasticities—extending beyond a one-year horizon. The structurally inferred disagreement should therefore be interpreted only as suggestive evidence of disagreement. Koijen and Yogo, 2019 propose the following logit demand curve for each investor $i$ and quarter $t$

$$\log \frac{w_{i,t}(n)}{w_{i,t(0)}} = \beta_{i,t}\mathrm{me}_t(n) + X_t(n)\beta_{i,t} + \epsilon_{i,t}(n) \tag{D.1}$$

which can be microfounded from mean-variance optimal portfolio choice under specific coefficient constraints. $\mathrm{me}_t(n) = \log \mathrm{ME}_t(n)$ is the market cap of stock $n$ and $X_t(n)$ includes the characteristics book equity, dividends-to-book equity, market beta, profitability, and investment. We estimate (D.1) via linear GMM using KY's mandate-based instrument and pooling investors with fewer than 1000 cross-sectional holdings by their assets under management. The moment condition is given by

$$\mathbb{E}_t[\epsilon_{i,t}(n)|\widehat{\mathrm{me}}_{i,t}(n), X_t(n)] \quad \text{s.t.} \quad \beta_{i,t} < 1 \quad \forall i, t.$$

where $\widehat{\mathrm{me}}_{i,t}(n)$ is the *investor-specific* counterfactual log market equity obtained if all *other* institutions (excluding $i$) held an equal-weighted portfolio given their investment universe. For each investor, stock, and date, we extract the quarterly demand shifts $u_{i,t}(n)$ from

$$u_{i,t}(n) = \Delta \log Q_{i,t}(n) - (\hat{\beta}_{i,t} - 1)\Delta \text{me}_{i,t}(n) \tag{D.2}$$

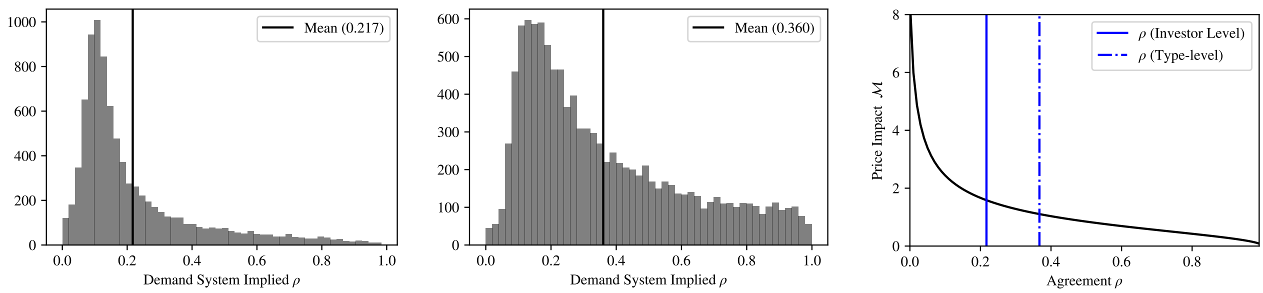
where $\Delta \log Q_{i,t}(n)$ and $\Delta \text{me}_{i,t}(n)$ are directly observable trades and changes in market equity, and $\hat{\beta}_{i,t}$ is the estimated coefficient on log market equity obtained from moment condition (D.4). Let $\tilde{u}_{i,t} = u_{i,t}(n) - \bar{u}_i(n)$ denote the time-series demeaned shifter, and $S_{i,t}(n) = \frac{w_{i,t}(n)A_{i,t}}{\sum_i w_{i,t}(n)A_{i,t}}$ the investor-level size-weights for each stock. We then compute stock-level measure of investor agreement as

$$\rho(n) = 1 - \frac{\sum_t \sum_i S_{i,t-1}(\tilde{u}_{i,t} - \tilde{u}_{S,t})^2}{\sum_t \sum_i S_{i,t-1}\tilde{u}_{i,t}^2} \tag{D.3}$$

where $\tilde{u}_{S,t}$ is the size-weighted average of the time-series demeaned shifters $\tilde{u}_{i,t}$. Panel a) of Figure D.2 plots the $\rho(n)$ for each stock. Because investor-level $\beta_{i,t}$ are estimated with considerable noise, which may artificially inflate the cross-investor variation in $u_{i,t}(n)$ and therefore artificially deflate $\rho(n)$, we also compute group-level $\hat{\beta}_{i,t}$ by averaging across investors with the same 13F typecode. We then infer $u_{i,t}(n)$ by plugging in the averaged type-specific $\hat{\beta}_{i,t}$ and compute the corresponding $\rho$ (Panel b). Panel c) plots the average $\rho$ along with the average bound for the cross-section of US stocks.

Figure D.2: **Implied Stock-level Agreement $\rho(n)$ from KY (2019)**
Panel a) plots distribution of stock-level $\rho(n)$ implied by KY using investor-specific elasticities. Panel b) plots distribution of $\rho(n)$ under elasticities that vary by investor type. Panel c) plots the average $\rho$ implied by KY along with the average bound.

(a) $\rho$ from Investor-level $\beta_{i,t}$ (b) $\rho$ from Group-level $\beta_{i,t}$ (c) Bound




## D.5 Flow-Induced Trades by Mutual Funds

Our construction of flow-induced trades by mutual funds closely follows Lou, 2012. We use quarterly mutual fund flows from the CRSP mutual fund survivorship-bias-free database. We set quarterly flows less than -100% or greater than 200% to missing and only include funds for which the total assets computed from their portfolio holdings are between 75% and 120% of the total net assets (TNA) reported by CRSP. Let $F_{i,t}$ denote the quarterly flow (in dollars) into fund $i$. Quarterly flow-induced demand is then simply given by summing over all hypothetical trades if flows were invested in line with previous portfolio weights $w_{i,t-1}(n)$:

$$FIT_t(n) = \frac{\sum_{i=1}^{I} F_{i,t} w_{i,t-1}(n)}{ME_{t-1}(n)} \tag{D.4}$$

where $ME_{t-1}(n)$ is the total market cap of stock $n$ as of the previous quarter.

# Appendix E Additional Figures and Tables

Figure E.1: **Portfolio Turnover versus Flow Volatility**
The figure plots the relationship between flow volatility $\sigma_q(n) = \sqrt{\sum_i S_i(n)\sigma_{q,i}^2(n)}$ and portfolio turnover $\sqrt{\frac{\pi}{2}}\mathbb{E}[\frac{\sum_i |\Delta Q_i|}{Q^*}]$, which are size-weighted averages of $\mathcal{L}_2$ and $\mathcal{L}_1$ norms respectively.

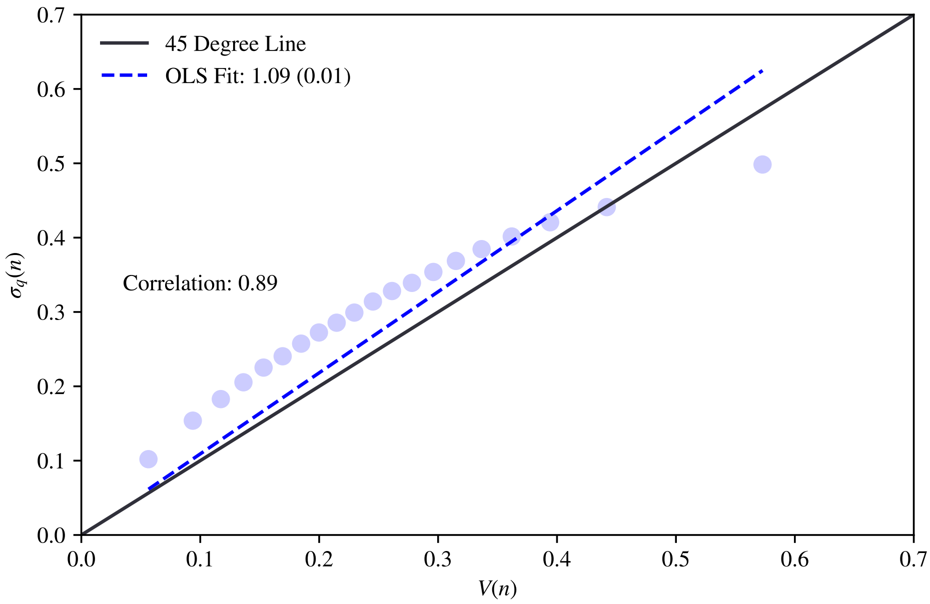


Figure E.2: **Empirical Relevance of $\rho$**

Panel a) plots the derivative $\frac{\partial \mathcal{M}}{\partial \rho} = -\frac{\mathcal{M}}{2\,\rho\,(1-\rho)}$ as a function of $\rho$ for the average US stock. Panel b) decomposes the variance of $\log \mathcal{M}_{\text{EPS}}$ into its underlying components $\log \sigma_p$, $\log \sigma_q$, and $\log \mathcal{D}$, where $\mathcal{D} := \sqrt{\frac{1}{\rho} - 1}$.

(a) $\frac{\partial \mathcal{M}}{\partial \rho}$ for varying levels of $\rho$ (b) Variance Decomposition of $\log \mathcal{M}_{\text{EPS}}$

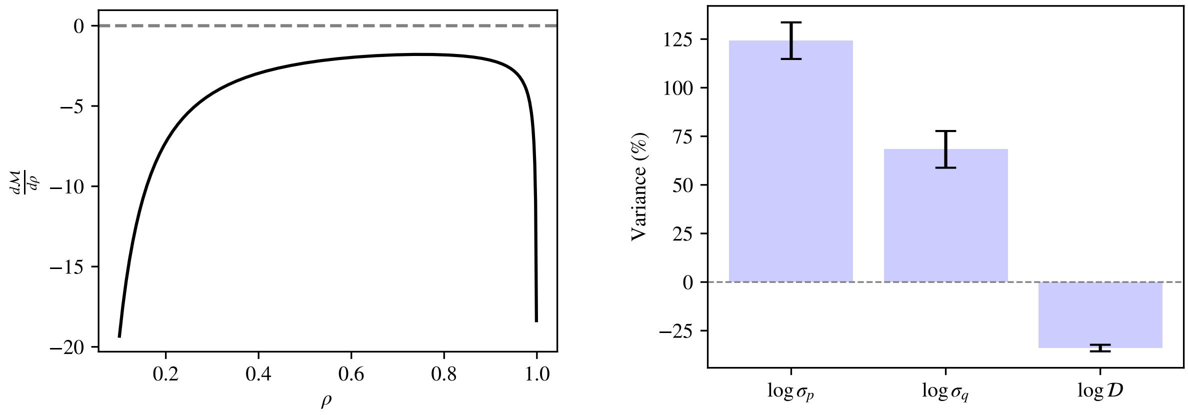



Table E.1: **Validation: Flow-Induced Trades**

The table summarizes the empirical validation of our bounds. We report the Panel coefficient of regressing quarterly stock-returns onto flow-induced trades (FIT) interacted with our bound $\mathcal{M}$, as well as the interaction with quintile dummies of $\mathcal{M}$. Formally, $r_t(n) = \alpha_t + \beta_1 FIT_t(n) + \beta_2 \mathcal{M}_t(n) + \beta_3\big(\mathcal{M}_t(n) \times FIT_t(n)\big) + \epsilon_t(n)$. T-stats are computed using standard errors clustered by date.

| | Dependent Variable: Returns | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| FIT | 3.820***<br>(0.510) | 2.635***<br>(0.636) | |
| $\mathcal{M}_{\text{EPS}}$ | | 0.004<br>(0.004) | |
| FIT × $\mathcal{M}_{\text{EPS}}$ | | 1.256*<br>(0.565) | |
| FIT × $\mathcal{M}_{\text{EPS}}$ quintile: 1 | | | 2.755***<br>(0.624) |
| FIT × $\mathcal{M}_{\text{EPS}}$ quintile: 2 | | | 3.175***<br>(0.588) |
| FIT × $\mathcal{M}_{\text{EPS}}$ quintile: 3 | | | 4.029***<br>(0.577) |
| FIT × $\mathcal{M}_{\text{EPS}}$ quintile: 4 | | | 4.152***<br>(0.718) |
| FIT × $\mathcal{M}_{\text{EPS}}$ quintile: 5 | | | 5.485***<br>(0.938) |
| Date FE | x | x | x |
| $\mathcal{M}_{\text{EPS}}$ quintile FE | – | – | x |
| Observations | 152,862 | 152,862 | 152,862 |
| $R^2$ | 0.249 | 0.250 | 0.250 |
| $R^2_{\text{Within}}$ | 0.004 | 0.005 | 0.005 |

Table E.2: **Validation: S&P500 Inclusions**

The table summarizes the price impact of index inclusions and their relationship with our bound. We report the coefficient of regressing (signed) abnormal event returns during S&P500 index reconstitutions onto the bound $\mathcal{M}$. T-stats are computed using standard errors clustered by date. Columns (1)–(3) report results for the full sample period, while columns (4)–(6) restrict the analysis to the pre-2000 subsample.

| | Dependent Variable: Abnormal Returns | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathcal{M}_{\text{EPS}}$ | | 0.058*<br>(0.025) | | | 0.110*<br>(0.046) | |
| $\mathcal{M}_{\text{EPS}}$ quintile: 1 | | | 0.046***<br>(0.014) | | | -0.015<br>(0.028) |
| $\mathcal{M}_{\text{EPS}}$ quintile: 2 | | | 0.082***<br>(0.024) | | | 0.058<br>(0.032) |
| $\mathcal{M}_{\text{EPS}}$ quintile: 3 | | | 0.073***<br>(0.016) | | | 0.082**<br>(0.028) |
| $\mathcal{M}_{\text{EPS}}$ quintile: 4 | | | 0.076***<br>(0.016) | | | 0.082**<br>(0.029) |
| $\mathcal{M}_{\text{EPS}}$ quintile: 5 | | | 0.140***<br>(0.024) | | | 0.174***<br>(0.039) |
| Intercept | 0.080***<br>(0.008) | 0.039<br>(0.021) | | 0.088***<br>(0.016) | -0.002<br>(0.039) | |
| Observations | 837 | 686 | 686 | 390 | 239 | 239 |
| $R^2$ | 0.021 | 0.036 | 0.040 | 0.038 | 0.091 | 0.096 |
| Adj. $R^2$ | 0.017 | 0.029 | 0.027 | 0.028 | 0.072 | 0.061 |

Table E.3: **Flow-Induced Trading: Alternative Impact Measures**

The table summarizes the coefficient of regressing quarterly stock-returns onto flow-induced trades (FIT) interacted with our price impact bound $\mathcal{M}$, the approximated price impact $\tilde{\mathcal{M}}$, and the gross turnover-based ratio $\frac{\sigma_p}{\sigma_q^{\text{Gross}}}$, as well as Amihud illiquidity. T-stats are computed using standard errors clustered by date.

| | Dependent Variable: Returns | | | |
|---|---|---|---|---|
| | $\mathcal{M}_{\text{EPS}}$ | $\tilde{\mathcal{M}}$ | $\frac{\sigma_p}{\sigma_q^{\text{Gross}}}$ | Amihud Illiquidity |
| | (1) | (2) | (3) | (4) |
| FIT | 2.635***<br>(0.636) | 2.505***<br>(0.622) | 3.376***<br>(0.574) | 3.772***<br>(0.568) |
| $\mathcal{M}$ | 0.004<br>(0.004) | 0.004<br>(0.005) | 0.023<br>(0.012) | -0.001***<br>(0.000) |
| FIT × $\mathcal{M}$ | 1.256*<br>(0.565) | 1.519*<br>(0.623) | 2.352<br>(1.277) | 0.014<br>(0.050) |
| Date FE | x | x | x | x |
| Observations | 152,862 | 152,862 | 152,862 | 152,862 |
| $R^2$ | 0.250 | 0.250 | 0.250 | 0.250 |
| $R^2_{\text{Within}}$ | 0.005 | 0.005 | 0.005 | 0.005 |

Table E.4: **S&P500 Inclusions: Alternative Impact Measures**

The table summarizes the price impact of index inclusions and their relationship with our measures. We report the coefficient of regressing (signed) abnormal event returns during S&P500 index reconstitutions onto the price impact bound $\mathcal{M}$, the approximated price impact $\tilde{\mathcal{M}}$, and the gross turnover-based ratio $\frac{\sigma_p}{\sigma_q^{\text{Gross}}}$. T-stats are computed using standard errors clustered by date.

| | Dependent Variable: Abnormal Returns | | | |
|---|---|---|---|---|
| | $\mathcal{M}_{\text{EPS}}$ | $\tilde{\mathcal{M}}$ | $\frac{\sigma_p}{\sigma_q^{\text{Gross}}}$ | Amihud Illiquidity |
| | (1) | (2) | (3) | (4) |
| $\mathcal{M}$ | 0.058*<br>(0.025) | 0.114***<br>(0.027) | 0.062<br>(0.046) | 0.008<br>(0.004) |
| log(ME) | -0.000<br>(0.013) | 0.008<br>(0.011) | 0.007<br>(0.013) | 0.003<br>(0.014) |
| $\beta$ | 0.009<br>(0.011) | 0.007<br>(0.010) | 0.018<br>(0.010) | 0.020<br>(0.010) |
| $\frac{\text{Dividend}}{\text{BE}}$ | 0.011<br>(0.008) | 0.005<br>(0.007) | 0.005<br>(0.007) | 0.008<br>(0.008) |
| Profit | -0.021*<br>(0.010) | -0.023*<br>(0.009) | -0.025**<br>(0.009) | -0.021*<br>(0.010) |
| Observations | 686 | 837 | 837 | 666 |
| $R^2$ | 0.036 | 0.049 | 0.025 | 0.027 |
| Adj. $R^2$ | 0.029 | 0.043 | 0.019 | 0.020 |

Figure E.3: **Price Impact at Different Horizons**

The figure plots the stock-level price impact $\tilde{\mathcal{M}}_H(n) = \frac{\sigma_{p,H}(n)}{\sigma_{q,H}(n)}$ for the average stock from 1990 to 2024. We construct $\tilde{\mathcal{M}}_H(n)$ using portfolio turnover and return volatility at the quarterly and annual frequencies. For the daily frequency, we use gross turnover as a proxy for portfolio turnover.