How Competitive is the Stock Market?

Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing*

Valentin Haddad
UCLA and NBER

Paul Huebner
Stockholm School of Economics

Erik Loualiche
University of Minnesota

March 13, 2024

Abstract

The conventional wisdom in finance is that competition is fierce among investors: if a group changes its behavior, others adjust their strategies such that nothing happens to prices. We estimate a demand system with flexible strategic responses for institutional investors in the US stock market. When less aggressive traders surround an investor, she adjusts by trading more aggressively. However, this strategic reaction only counteracts two thirds of the impact of the initial change in behavior. In light of these estimates, the rise in passive investing over the last 20 years has made the demand for individual stocks 11% more inelastic. *JEL Codes: G1, G2, D4, L1.*

*Haddad: vhaddad@ad.ucla.edu. Huebner: paul.huebner@hhs.se. Loualiche: eloualic@umn.edu. We are thankful for useful comments by Hengjie Ai, Philip Bond, Hui Chen, Judith Chevalier, Alex Chinco, Carole Comerton-Forde, Shaun Davies, Victor DeMiguel, Xavier Gabaix, Sergei Glebkin, Matthieu Gomez, Johan Hombert, Harrison Hong, Marcin Kacperczyk, Ralph Koijen, Peter Kondor, Hanno Lustig, Mina Lee, Rob Richmond, Marco Sammon, Dimitri Vayanos, Laura Veldkamp, Moto Yogo and seminar participants at CU Boulder, Unil/EPFL, Harvard Business School, Insead, Minnesota Carlson, Nova, SAIF, Stockholm School of Economics, NYU, Princeton University, UCLA, University of Maryland, USC, Washington University in Saint Louis, UIC, WU Vienna, University of Wisconsin at Madison, Virtual Finance Workshop, Asian Finance Association meetings, EUROFIDAI, NBER Asset Pricing Summer Institute, NBER Long-Term Asset Management, PHBS Workshop, UBC Winter Finance, Adam Smith Workshop, SFS Cavalcade, HEC-CEPR Conference, LSE Dysfunctional Finance Conference, WFA, NBER Industrial Organization Summer Institute, Minnesota Macro Workshop, EFA, Q Group Fall Seminar, and AFA. Haddad acknowledges financial support from the Fink Center for Finance and Investments at UCLA Anderson.

1 Introduction

What happens to equilibrium prices when a subset of investors changes its behavior? For example, what are the implications of investors switching to passive strategies, which has occurred on a large scale over the last few decades?[1] Answering such questions relies crucially on how other investors react to changes. Under the common view that financial market participants compete fiercely with each other, the answer is simple: nothing happens, because other investors pick up any slack left by those changing their behavior.[2] Casually said: if you stop looking for $20 bills on the floor, someone else will replace you. This paper proposes a framework to quantify these strategic responses, combining information from prices and portfolio positions. We implement the framework for the US stock market and study its implications for the rise of passive investing.

We find that investors react to the behavior of others in the market: when an investor is surrounded by less aggressive traders—that is, with a lower price elasticity of demand—she trades more aggressively. While this reaction mitigates the equilibrium consequences of changes in individual behavior, it is not nearly as strong as in the common view of irrelevance of market organization. For instance, our estimates suggest that this strategic response reduces the direct impact of an increase in passive investing by two thirds. An increase as large as the one observed over the last 20 years leads to substantially more inelastic aggregate demand curves for individual stocks, by 11%.

To get to these answers, we proceed in three steps. Intuitively and in line with many theories, we first formalize the degree of strategic response between investors: how much does my demand elasticity respond to the elasticity of others? When investors compete strongly for trading opportunities, their strategies respond more to how others are trading. Second, we provide a framework to quantify these strategic responses and their implications for prices. We write down a demand system (à la Koijen and Yogo (2019)) where not only prices but also demand elasticities are the

[1]For example, the ICI factbook (Investment Company Institute, 2020) reports that the total assets of passive mutual funds in the U.S. have increased from $11b to $2.8t between 1993 and 2020.

[2]In his discussion of Fama's work on efficient markets, Cochrane (2013) emphasizes how intensely financial market participants look for investment opportunities: "other fields are not so ruthlessly competitive as financial markets." Thaler (2015) also discusses the common view among economists that even if investors blunder, prices fix themselves in equilibrium, what he calls the "invisible handwave argument." While rarely formalized, this view underlines most of the literature assuming away the structure of the financial sector and focusing on representative agent models.

equilibrium result of investors' interactions. Third, we estimate the model using detailed portfolio positions of institutional investors in the US stock market. We quantify the impact of a rise in passive investing and decompose the sources of evolution in demand for individual stocks.

Why is the degree of strategic response so central to financial markets? A more elastic demand curve implies more aggressive trading: the investor increases their position a lot when the asset is cheap. In standard price theory, only a consumer's preferences determine their demand elasticity; your demand for apples depends on how you trade off money and apples. In contrast, an investor's choice of elasticity in financial markets also depends on the behavior of other investors. If others are not trading aggressively, investment opportunities arise, and you have more incentives to trade aggressively. In an idealized view, there is always somebody on the lookout for good deals, and this response is so strong that it compensates for any initial change in investor behavior. In practice, many aspects limit the strength of this reaction. Changing your strategy might require new information to identify profitable trades (Grossman and Stiglitz, 1980), overcoming contractual frictions (e.g. investment mandates) that limit flexibility in setting trading strategies, having incentives to maximize risk-adjusted returns (Chevalier and Ellison, 1997), or having high cognitive sophistication (Eyster et al., 2019). More generally, investors face limits to arbitrage (Shleifer and Vishny, 1997). Finally, while the issue of how investors compete in setting their trading strategies is distinct from whether there is perfect competition for the asset (price-taking behavior), market power also weakens the degree of strategic response (Kyle, 1989).[3] Despite their pervasiveness in the theoretical literature, strategic responses have been absent from the recent literature building empirical equilibrium models of investor demand.[4]

We entertain all of these mechanisms by taking a semi-structural approach: investors follow exogenous but flexible investment strategies, and the market must be in equilibrium. We assume that each investor's demand elasticity combines an investor-specific component and a reaction to the aggregate demand elasticity prevalent in the market. The degree of strategic response is the intensity of this reaction. An equilibrium combines two layers. First, the elasticities of all investors

[3] Going back to Kreps and Scheinkman (1983), it is understood that price-taking is not the only aspect shaping competition.

[4] As such, our framework addresses a common Lucas critique of these models that the demand for assets is not a fixed characteristic of investors.

must be consistent with each other: the average of all investor elasticities must be equal to the aggregate elasticity. Second, the asset price is such that the sum of all demand curves evaluated at this price equals the supply of the asset. The simplicity of this framework does not impede its richness. We show that all of the aforementioned foundations for investor strategic responses map to the structure of our model.[5]

What happens when a group of investors becomes passive? Their investment strategy turns irresponsive to the price of the asset; hence their demand elasticity goes to zero. This change pushes the aggregate elasticity down, prompting other investors to respond, potentially compensating for the direct effect. When the strategic response is strongest, this reaction completely offsets the direct effect. The equilibrium market elasticity remains unchanged, and so is the behavior of the asset price. This situation corresponds to the null hypothesis of "fiercely competitive financial markets." On the other extreme, if investors do not react, the elasticity provided by the traders who became passive is just lost. More generally, we derive a simple formula for the pass-through of a rise in passive-investing to aggregate elasticities as a function of the degree of strategic response.

We parametrize the demand system in the style of Koijen and Yogo (2019) to take it to the data. In particular, the specification entertains rich heterogeneity across investors. However, unlike in Koijen and Yogo (2019), one cannot independently estimate the demand of each institution. Because of the strategic response, the demand elasticities of all investors are intertwined and must be solved simultaneously. This elasticity equilibrium creates three challenges that we overcome.

First, the interaction between investors through their elasticity decisions introduces a reflection problem (Manski, 1993): a market with high elasticity could result from either high individual elasticities or strong positive spillovers. The cross-section of stocks provides a solution to this issue: the same investor faces a different mix of competing investors for each stock, therefore a different aggregate demand elasticity. This variation allows us to isolate the spillover from the individual-specific component of elasticity. This argument faces a chicken-and-egg question. We need to know the elasticities of other investors to implement this comparison. But estimating these investors' elasticities requires knowing the initial investor's elasticity in the first place. We derive

[5] Vives (2011) and Rostek and Weretka (2012) are theoretical antecedents of this approach by formalizing the notion of equilibrium in linear demand schedules when there are finitely many players and market power.

and verify conditions on the graph of investor-stock connections under which these problems can be solved simultaneously.

Second, both the price and the aggregate elasticity are equilibrium quantities and therefore depend on portfolio decisions, leading to an endogeneity challenge in demand estimation. We construct an instrument for each of these variables using variations in investment universe across investors. Stocks that more investors can buy naturally have more money chasing them and a higher price, an instrument introduced in Koijen and Yogo (2019). For the aggregate elasticity, we introduce a new model-based instrument combining the variation in investment universe with the estimated individual component of elasticities.

Third, the inclusion of rich investor heterogeneity, the need to solve for an elasticity equilibrium, and the presence of a model-based instrument all concur to a seemingly intractable estimation. We develop a computationally efficient algorithm that estimates the model.

Our estimates suggest a substantial amount of strategic response. If the aggregate elasticity for a stock increases by 1, an individual investor decreases her elasticity of demand by 3. We confirm the robustness of this finding to deviations from our identification assumptions in a battery of specifications: alternative constructions of the instruments, more weights on large investors, additional controls, etc. Across these specifications, the estimated strategic response remains between 2.30 and 3.27. The positive value of χ supports theories of strategic responses emphasizing substitutability (e.g., based on endogenous information acquisition) rather than complementarity (e.g., based on market power). This competition among investors stabilizes the levels of aggregate elasticity. Intuitively, when a very aggressive investor trades a specific stock, other investors in this stock adjust by becoming less aggressive. This force implies about 50% less cross-sectional variation in elasticity across stocks than estimates that ignore strategic interactions, highlighting the importance of these interactions.

We use these estimates to assess the impact of a rise in passive investing. To do so, we ask how equilibrium elasticities change when a fraction of investors exogenously becomes passive. We obtain a simple formula for the pass-through of a change in the fraction of active investors to the aggregate elasticity. This pass-through solely depends on the degree of strategic response and the initial fraction of active investors. It is decreasing in both quantities. Empirically, we find this pass-through to be about 0.33. A third of a change in the fraction of active investors translates into a reduction in demand elasticity. Given the 32% decrease in active investing over the last 20 years that we observe in the data, this effect yields a reduction in elasticities of 11%. This is a sizable change: in the context of many models, it would lead to less informative and more volatile prices, as well as more price impact — we confirm these connections empirically in the cross-section. This result is our main empirical conclusion: while the effects of competition in strategies are strong, the stock market is far from the common view.[6]

A potential concern is that the model ignores some forces to maintain tractability. For example, some theories predict that the strategic response depends on who is switching to passive investing beyond their initial elasticity. Or, these interactions could occur not only through existing investors changing their strategies but also through the entry or exit of new investors. To assess the presence of these other mechanisms, we regress changes in aggregate elasticity on changes in passive investing at the stock level, zooming in on several sources of variation. Confirming our model estimate, we find a pass-through of about a third irrespective of whether we include stock or date fixed effects or even instrumenting for passive investing using index inclusions.

The model also provides an account of the actual evolution of the demand for stocks over the last 20 years. Our model finds two important sources of changes in elasticity. First, the fraction of passive investors has increased steadily over our sample. Second, the investor-specific component of the elasticity of active investors has also experienced significant changes: initially increasing until 2007, then trending downwards, and dropping overall. This second dimension is interesting because it suggests a role for market-wide shifts in individual strategies beyond the rise of passive investing, such as developments in computing power and access to big data.[7] The presence of these other long-term changes in investor behavior also highlights the danger of assessing theories of the impact of passive investing purely based on aggregate trends, an issue that our structural approach steers clear of. We also find that strategic responses played an important role: active investors also increased their equilibrium elasticity in response to the broad decrease in aggregate

[6]In this case, the pass-through is 0: a rise in passive investing has no impact. On the other hand, without strategic effects, the pass-through is 1, leading to a 32% decrease in elasticity.

[7]Farboodi and Veldkamp (2020) develop a theory of the effect of growth in financial data technology.

elasticities. In a counterfactual exercise in which we shut down the strategic responses, we find that elasticities would have decreased about twice as much. In contrast, with strong strategic responses they would have barely moved.

Taken together, our results highlight the importance of a more nuanced approach to how investors compete in financial markets. No, it is not the case that "financial markets are fiercely competitive" and that all shocks are fully absorbed by other investors. But also, no, it does not mean that investors do not interact at all. This framework is a first step towards quantifying the degree of strategic response and its implications. Our estimates suggest that these interactions played an essential role in shaping the response to the rise of passive investment. This strategic response is likely important for many other questions about investor demand; we sketch the implications of our framework beyond the rise in passive investing. What happens when a large set of financial institutions must change their trading because of new regulations? What happens when some sophisticated specialized investors get in financial trouble?

Contribution to the existing literature. The idea that investors compete with each other when choosing their strategies has a long history in finance. Grossman and Stiglitz (1980) first formalize the notion of competition for information between investors and show it does not lead to informationally efficient markets.[8] Kyle (1989) highlights how market power also creates interactions among investors. These seminal contributions have led to a large theoretical literature pointing out rich ways in which investors react to each other and choose their trading strategies. Veldkamp (2011) and Rostek and Yoon (2023) review the work on information and market power, respectively. In the context of the rise of passive investing, Subrahmanyam (1991) is an early contribution highlighting liquidity concerns. More recent work includes Bond and García (2018), Malikov (2019), Lee (2020), Buss and Sundaresan (2020), and Kacperczyk et al. (2020). Kacperczyk et al. (2016) focus on cyclical changes in investor attention. Gârleanu and Pedersen (2018) and Gârleanu and Pedersen (2021) focus on the interaction between the market for asset managers and the market for assets. Farboodi and Veldkamp (2020) focus on the choice between

[8] Coles et al. (2022) show that an increase in passive investing does not affect price informativeness in this baseline model.

information about fundamentals or about demand in the context of the rise in big data. However, these theories are rarely confronted to portfolio data. Our new approach, summarizing strategic responses through choices of demand elasticity, allows us to bring the theory to the data.

We also contribute to a recent literature on estimating demand systems accounting for the large heterogeneity in portfolio holdings, started by Koijen and Yogo (2019). Koijen et al. (2021), Koijen and Yogo (2020), Koijen et al. (2020), Jiang et al. (2020), van der Beck (2022) and Huebner (2023) also apply this approach. Balasubramaniam et al. (2021) estimate a factor model of portfolio holdings. Dou et al. (2020) study how mutual funds change their portfolios in response to common fund flows. Gabaix and Koijen (2020) estimate the aggregate demand for stocks. Our key innovation on that front is to incorporate strategic interactions between investors, a long-theorized feature we find to be quantitatively important.

More broadly our paper relates to a wider literature studying the relation between portfolio quantities and asset prices. De Long et al. (1990) argue that noise trader shocks can affect prices. These ideas have found applications across multiple asset classes: stocks (Shleifer (1986), Warther (1995)), government bonds (Vayanos and Vila (2021), Greenwood and Vayanos (2014), Haddad and Sraer (2020)), options (Gârleanu et al. (2009)), currency markets (Gabaix and Maggiori (2015), Greenwood et al. (2019), Gourinchas et al. (2019)), or corporate bonds (Haddad et al. (2021)). While our estimates concentrate on the stock market, we bring to the forefront the importance of strategic interactions between investors, which likely also matter in other markets.

Finally our results provide new insights in the debate on the consequences of the long-term rise in passive investing. French (2008) and Stambaugh (2014) provide empirical evidence of a shift towards passive investing. Zooming in on portfolios, we uncover how passive investing is altering how all investors trade and therefore its equilibrium implications. Other work focuses on quasi-natural experiments around index or ETF inclusion such as Chang et al. (2014), Ben-David et al. (2018), or Coles et al. (2022). Sammon (2021) studies the response of stock prices around earnings announcements. Bai et al. (2016), Dávila and Parlatore (2018), and Farboodi et al. (2021) document long-term trends in price informativeness.

2 An Equilibrium Model of Financial Markets with Investor Competition

We present our framework of investor interactions in financial markets. The key idea is that there are two layers to an equilibrium in financial markets. First, the price is such that the sum of investor demands equals the supply of the assets. Second, investors compete with each other in setting their strategies: they choose how aggressively they trade as a function of how others trade. This aggressiveness is measured by their demand elasticity. First, we introduce the two layers, then we highlight the implications of our framework for the rise of passive investing. Table 1 summarizes the model.

2.1 First layer: the asset price clears the market given demand curves

For the sake of simplicity, we focus on the case of a single asset in fixed supply S and a continuum of investors indexed by i. We generalize to multiple assets when moving to the data in Section 4. In an equilibrium, each investor decides how many shares they buy as a function of the price P of the asset: a demand curve $D_i(P)$, which we can log linearize around a baseline value for the price $\bar{P}$:

$$d_i = \underline{d}_i - \mathcal{E}_i \times (p - \bar{p}), \tag{1}$$

where lowercase letters represent log values.[9] The elasticity of this demand curve, $\mathcal{E}_i$, determines how aggressive the investor is.[10] An investor with $\mathcal{E}_i = 0$ does not react to changes in prices, while an investor with large $\mathcal{E}_i$ increases her position a lot when the asset is cheap. Beyond the price, other aspects can also affect the choice of positions. For example, an investor could care about the risk profile of the asset or have a preference for environmental, social, and governance (ESG) investing. We collect these other aspects inside the constant $\underline{d}_i$; the empirical analysis will be more flexible about modeling $\underline{d}_i$.

[9]The assumption of demand curves does not necessarily imply price-taking. For example, in the rational expectation equilibrium with imperfect competition of Kyle (1989), investors also post demand curves.
[10]Similarly Gabaix and Koijen (2020) consider log-linear demand curves around a reference price level.

Table 1. The 2-layer model of asset market.

	Individual Decision	Equilibrium Condition
Demand	$d_i = \underline{d}_i - \mathcal{E}_i \times (p - \bar{p})$	$\int D_i(p) = S$
Elasticity	$\mathcal{E}_i = \underline{\mathcal{E}}_i - \chi \times \mathcal{E}_{agg}$	$\int \mathcal{E}_i D_i / S = \mathcal{E}_{agg}$

Investors' elasticities play an important role in the determination of equilibrium prices. The aggregate demand curve is $D_{agg}(P) = \int D_i(P)$, and the equilibrium price solves $D_{agg}(P^*) = S$. Aggregate demand has elasticity

$$\mathcal{E}_{agg} = \frac{\int \mathcal{E}_i D_i}{\int D_i}. \tag{2}$$

The (holdings-weighted) average of individual elasticities measures how strongly aggregate demand for the asset responds to the price. This aggregate elasticity shapes the behavior of the equilibrium price. If investors are very aggressive, aggregate demand is perfectly elastic, $\mathcal{E}_{agg} \to \infty$, and prices are pinned down at a fixed level. In such a situation, changes in individual investor characteristics $\underline{d}_i$ or in supply S do not affect the price. This is what people sometimes describe as "efficient markets:" any deviation of the price from a fundamental value is immediately traded away by aggressive investors. On the other hand, when demand is more inelastic, small changes in the market structure can have a large effect on prices because investors are unwilling to change their positions.

For example, if elasticities are constant, a small uniform change $\Delta\underline{d}$ to the demand of all investors results in a price change of

$$\Delta p = \mathcal{E}_{agg}^{-1} \times \Delta\underline{d}. \tag{3}$$

If all investors want to increase the size of their position by one percent, the price increases by the multiplier $M_{agg} = \mathcal{E}_{agg}^{-1}$ percent. Consequently, more inelastic markets experience larger price variation due to changing investor demands, and are therefore more volatile.[11] A change in supply would have the opposite effect on the price with a multiplier $-M_{agg}$. More fleshed-out models such as the ones we present in Section 3 also relate the aggregate elasticity to other equilibrium properties such as price informativeness, liquidity, or limits to arbitrage. We confirm these relations empirically in Section 6.3.2.

2.2 Second layer: investors set their demand elasticity in response to others

In standard price theory, the elasticity of demand reflects only an individual's preference for a good. In particular, it does not depend on the decisions of other market participants. When choosing how many apples to put in your shopping cart, it does not matter what other shoppers are doing beyond their effect on the price level. However, in financial markets, it matters why the price is moving and consequently demand elasticities are not fixed.[12] Investors compete for trading opportunities. For example a common theoretical prediction is that, if many investors trade aggressively, fewer good deals are available; therefore, there are also fewer incentives to trade with a high elasticity.

This relation adds a second layer to the equilibrium, which captures how investors compete when choosing their strategies. At the individual level, the elasticity responds to the aggregate demand elasticity. But conversely, the aggregate demand elasticity is an average of individual elasticities. Formally, we represent this feedback by endogenizing individual demand elasticities as a function of the aggregate demand elasticity:

$$\mathcal{E}_i = \underline{\mathcal{E}}_i - \chi \, \mathcal{E}_{agg}. \tag{4}$$

The parameter χ controls the strength of the response to the aggregate elasticity; it measures the

[11] See also Gabaix and Koijen (2020) for a discussion of the role of the elasticity of aggregate demand in financial markets.

[12] A similar phenomenon arises in auction settings: a bidder's optimal bidding strategy often responds to the strategies of other participants in the auction.

extent of strategic substitution in demand elasticities.[13] $\underline{\mathcal{E}}_i$ is a baseline level of elasticity reflecting the investor's own preferences for the asset, for example shaped by her risk aversion or her beliefs about the payoffs. Together, the individual decision equation (4) and the aggregation condition of equation (2) pin down the equilibrium of elasticities.

We refer to the parameter χ as the *degree of strategic response*. Large values of χ capture the narrative that "financial markets are fiercely competitive." If a group of sophisticated investors goes away, other investors pick up the slack by trading more aggressively. In the extreme case where χ goes to infinity, the strategic response is so strong that the equilibrium aggregate elasticity $\mathcal{E}_{agg}$ is pinned down at a fixed level.[14] Changes in individual investor behavior or the composition of investors do not affect the aggregate elasticity.

On the other hand, when $\chi = 0$, individual investors do not respond to the aggregate elasticity. We are back to standard price theory: each investor follows a strategy that is independent of the actions of other investors. Under this view, if a group of sophisticated investors goes bankrupt, nobody else steps in to take advantage of the opportunities that are left untouched: the aggregate elasticity drops sharply.

The parameter χ offers a simple and flexible way to capture strategic interactions and their consequences. We do not take a stand on a specific microfoundation for the parameter χ. In many theories, demand elasticities are a key feature of investors' strategies and exhibit substitutability or complementarity; we devote Section 3 to these theories.[15] Rather than restricting ourselves to a specific foundation — many of these theories are operating side by side — we measure strategic responses directly from trading and portfolio data.

This specification of strategic responses implies a few restrictions relative to a completely general setting. First, it assumes that the aggregate demand elasticity is a sufficient statistic for what aspect of others' strategies investors respond to. This feature arises in the examples of Section 3; it is also an assumption in the equilibria as a fixed point in price impacts of Vives (2011),

[13]We consider strategic substitutes and complements in the sense of Bulow et al. (1985) and defined in chapter 4 of Veldkamp (2011).

[14]Equation 4 might suggest that elasticities are lower when χ is large, but it is not necessarily the case, as economies with a large χ will tend to also have a large $\underline{\mathcal{E}}_i$. See for example the calculation in the next section.

[15]Technically, other aspects of investor decisions may be the source of substitutability (e.g. information acquisition or social interactions). However, because elasticities are directly related to these other decisions, the substitutability manifests itself in the demand elasticity.

Rostek and Weretka (2012) and Rostek and Yoon (2023). Second, we assume that all investors have the same degree of strategic response χ. We make this choice for the sake of tractability in estimation. Appendix A.4 discusses how the model changes with investor-specific χ, and Section 5.2 implements diagnostics that confirm that this assumption is not consequential for our inference. Third, this model does not feature strategic entry and exit of investors, or, when we turn to the data, flows in and out of specific institutions. The tests of Section 6.3.1 suggest that this extensive margin is not substantial in our application, which focuses on the demand for individual stocks.[16] However, it might be more relevant when considering changes in the aggregate demand for stocks or broad asset classes, with larger movements following the performance of broad asset classes.

Next, we show how the degree of strategic response plays a crucial role in several applications. First, we study the effect of a rise in passive investing — our main empirical application. Second, we show that understanding how institutions react to each other in setting their strategies is central for intermediary asset pricing. Finally, Appendix Sections A.2 and A.3 consider implications for the asymmetry of mispricing and the dynamics of limits to arbitrage.

2.3 The effect of a rise in passive investing

Accounting for strategic responses is essential in evaluating the effect of a rise in passive investing. Consider the following thought experiment. We start from an economy with homogeneous investors who, in this initial equilibrium, have elasticity $\mathcal{E}_i = \mathcal{E}_0$. The aggregate elasticity is therefore also $\mathcal{E}_0$. What happens when a fraction $1 - \alpha$ of these investors becomes passive, that is keep the same holdings, but reduce their elasticity to zero?

The direct effect of this change is that now only a fraction α of investors contribute to the aggregate elasticity. If we only consider this effect, the aggregate elasticity decreases to $\mathcal{E}_{agg} = \alpha \mathcal{E}_i$ (from the aggregation equation (2)). But the story does not end here; the remaining active investors adjust their strategies. This is exactly what the degree of strategic response χ captures. Active investors change their own elasticity in response to the aggregate: $\Delta \mathcal{E}_i = -\chi \Delta \mathcal{E}_{agg}$ (from equation (4)). This response compensates the direct effect when $\chi > 0$. Each active investor

[16] Relatedly, Azarmsa and Davis (2023) find much stronger elasticity of demand within institution than at the extensive margin across institutions.

responds again to the response of other active investors, until they reach a new equilibrium.[17] Appendix Figure IA.2 illustrates this process. The new aggregate elasticity is:

$$\mathcal{E}_{NEW} = \underbrace{\alpha\mathcal{E}_0}_{\text{direct effect}} + \underbrace{(1-\alpha)\mathcal{E}_0 \frac{\alpha\chi}{1+\alpha\chi}}_{\text{strategic response}}. \tag{5}$$

With a large degree of strategic response, χ is large, and $\mathcal{E}_{NEW} = \mathcal{E}_0$, the aggregate elasticity is unchanged. The drop in elasticity due to the investors that became passive is exactly compensated by a greater elasticity of the remaining active investors. In contrast, when investors are insensitive to market conditions, χ close to zero, only the direct effect operates, and the elasticity declines by a factor α.

What does this imply quantitatively? Over the last 20 years, the fraction of active investors has decreased by about 30%, so we set $\alpha = 70\%$.[18] In the estimation of Section 4, we find a degree of strategic response χ of 3. This implies that the initial elasticity is multiplied by a factor of $70\% + 30\%(70\% \times 3)/(1 + 70\% \times 3) = 0.90$. The rise of passive investing leads to a substantial drop in elasticity of 10%. This is a third of the direct effect that would have led to a decrease of 30%. However, it is still much more than the zero predicted by the common view.

In Section 4, we fully specify our framework to account for heterogeneity across investors and stocks, and estimate it using portfolio holdings data.[19] This allows us to revisit the question of the rise in passive investing in the context of a realistic quantitative model in Section 6.1.

2.4 Intermediary asset pricing

How do markets change when some financial institutions get distressed or when they are more tightly regulated? As these institutions trade less aggressively they provide less elasticity to the market and we expect more unstable prices. Two aspects shape this response: how large the direct shock to the institutions is, but also how other competing investors respond. Consider how

[17]Formally, we do not model this tâtonnement, and instead focus directly on equilibria. We present details of the calculation in Appendix Section A.1.

[18]Section 6.1 reviews estimates of this quantity.

[19]Appendix Section A.4 shows that when χ differs across investors, what matters for the rise of passive investing is the demand-weighted average value among active investors.

the aggregate elasticity responds to a combination of shocks to individual elasticities $\{\Delta \underline{\mathcal{E}}_i\}_i$; for example, only the affected institutions receive a negative shock to their elasticity. For simplicity, we assume that the price is at its baseline, $p = \bar{p}$, and leave the general case to Appendix A.[20] We show that the change in the aggregate elasticity is

$$\Delta \mathcal{E}_{agg} = \frac{1}{1+\chi} \mathbf{E}[\Delta \underline{\mathcal{E}}_i], \tag{6}$$

where $\mathbf{E}[.]$ denote the demand-weighted population average.[21] The change in aggregate elasticity combines the average direct elasticity shock $\mathbf{E}[\Delta \underline{\mathcal{E}}_i]$ and a mitigating factor due to the strategic response $1/(1+\chi)$. With strong responses, $\chi \to \infty$, the shock to some investors has no effect on the aggregate elasticity. This is the view of those arguing that intermediaries cannot matter for asset prices. However, for lower values of χ, the direct effect is not mitigated. Theoretical models centered on intermediaries often assume $\chi = 0$ (e.g He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2013)).

As such, when analyzing how the financial health of intermediaries matters for asset pricing and the economy, one must also take into account how other institutions compete with them. Consistent with this idea, Haddad and Muir (2021) show that in markets that are more sophisticated and hence with less intense competition, periods of distress in the financial sector are associated with stronger movements in risk premium. Eisfeldt et al. (2017) also emphasize this role of investor competition in markets for complex assets such as mortgage-backed securities. Siriwardane et al. (2021) document many situations in which shocks to one intermediary are imperfectly compensated by the reaction of other intermediaries.[22]

[20] Unlike in the precedent calculation, we assume that there are no passive investors.

[21] Formally this corresponds to

$$\mathbf{E}[x_i] = \int x_i \frac{D_i}{S}.$$

[22] Other examples of large effects of intermediary health in specialized markets include Gabaix et al. (2007) and Siriwardane (2019).

3 The Origins of Strategic Interactions in Financial Markets

In an idealized view of financial markets, investors are constantly on the lookout for good opportunities, and swiftly come in if another market participant steps down. This corresponds to $\chi \to +\infty$ in our framework. In practice, many forces limit this process of strategic response. We discuss the most prominent ones in this section: costly information acquisition, bounded rationality, liquidity, peer effects. Appendix Section C discusses the role of institutional frictions and endogenous risk. We show that our 2-layer equilibrium model captures the main insights of these theories in a parsimonious way.

3.1 Costly information acquisition

A basic idea of how investors interact with each other is that if some active investors exit the market, there are more investment opportunities to take advantage of, and other investors go after them by trading more aggressively. In practice, knowing that there are more investment opportunities is not enough, investors have to evaluate them. The costs of this process of learning (information gathering, hiring analysts, etc.) naturally limit the ability to compete.

We formalize this intuition in a model in the style of Grossman and Stiglitz (1980) with information acquisition as in Veldkamp (2011), and show it maps tightly to our two-layer equilibrium.[23] We focus here on the main results and leave details of the setting and derivations to Appendix B.

There is one period and one asset, and a continuum of agents indexed by i. Each agent has CARA preferences with risk aversion ρ_i. The gross risk-free rate is 1, and the (random) asset payoff is f. The asset is in noisy supply $\bar{x}+x$ with $\bar{x}$ a fixed value and $x \sim \mathcal{N}(0, \sigma_x^2)$. Initially, each agent is endowed with an independent signal μ_i of the fundamental f, distributed $\mu_i \sim \mathcal{N}(f, \sigma_i^2)$.[24] Obtaining more precise signals is more costly. Each agent can acquire an additional private signal

[23] Bond and García (2018) and Malikov (2019) provide theoretical analyses of the rise of passive investing in this family of theories.

[24] Following Veldkamp (2011), we assume agents start with a flat prior on f, hence their initial belief is $f \sim \mathcal{N}(\mu_i, \sigma_i^2)$.

$\eta_i \sim \mathcal{N}(f, \sigma^2_{i,\eta})$ at monetary cost $c_i(\sigma^{-2}_{i,\eta} + \sigma^{-2}_i)$, with $c_i(.)$ a non-decreasing positive function.[25] The signal being private implies in particular that signal realizations are uncorrelated across agents conditional on the fundamental f.

Optimal asset demand is linear in the price: $d_i = \underline{d}_i - \mathcal{E}_i p$.[26] The slope of the demand curve characterizes how aggressively an investor changes her portfolio when the price moves. We find (Appendix B.3):

$$\mathcal{E}_i = \frac{1}{\rho_i} \left(\sigma_i^{-2} + \sigma_{i\eta}^{-2} \right). \tag{7}$$

Two elements shape the investor's demand elasticity: her risk aversion and her private information. An investor with more precise information about the asset is more confident in her forecast of the asset returns, and therefore trades more aggressively. Looking ahead, we can already see that constraints to the ability to change information acquisition will limit the ability of the investor to change her elasticity.

Before that, we show that the aggregate elasticity, $\mathcal{E}_{agg} = \int_i \mathcal{E}_i di$, is the appropriate notion for how the collective actions of all investors shape the price. In equilibrium, the price follows

$$p = A + f - \mathcal{E}_{agg}^{-1}\, x, \tag{8}$$

where A is a constant. The price responds one-to-one to the fundamental f, but is also affected by noise trading x. The aggregate elasticity controls the impact of noise: if everybody trades aggressively against abnormal price movements, noise traders cannot push the price far away from fundamentals. In line with this intuition, a market with higher aggregate elasticity also has less volatile returns ($\text{Var}(f - p) = \mathcal{E}_{agg}^{-2} \sigma_x^2$) and more informative prices ($\text{Var}(f|p)^{-1} = \mathcal{E}_{agg}^2 \sigma_x^{-2}$).

The strategic responses of investors to one another occur through information choices. The aggregate elasticity impacts price dynamics, which in turns affect the incentives to acquire infor-

[25] This parametrization is without loss of generality relative to a cost function that would only depend on the acquired signal $\sigma_{\eta,i}$.

[26] For all of this subsection, we do a small abuse of notation: lowercase letters represent levels rather than logarithms and $\mathcal{E}_i$ denotes the slope of the demand curve, rather than the elasticity stricto sensu. This approach lends itself to the linearity of the CARA-Normal framework, but is less appealing for empirical applications. Petajisto (2009) finds that such linear models lead to counterfactually high elasticities of the order of 6250.

mation and trade in an elastic way. When choosing how much information to acquire, investors trade off the cost of a more precise signal with the benefit of a more informed trading strategy. The utility gain from precise information is proportional to knowledge of the fundamental, which combines private information (corresponding to $\mathcal{E}_i$) and information learned from prices (corresponding to $\mathcal{E}_{agg}$). Focusing on elasticities, this leads to the following optimization problem:

$$\max_{\mathcal{E}_i} \frac{1}{2} \log \left(\rho_i \mathcal{E}_i + \mathcal{E}_{agg}^2 \sigma_x^{-2}\right) - \rho_i c_i(\rho_i \mathcal{E}_i) \tag{9}$$

This problem is the counterpart to equation (4): the choice of individual elasticity $\mathcal{E}_i$ depends on the aggregate elasticity $\mathcal{E}_{agg}$. To a first-order approximation, the degree of strategic response is the sensitivity of the optimal individual elasticity to the aggregate elasticity: $\chi = -\partial \mathcal{E}_i / \partial \mathcal{E}_{agg}$.[27] In this model, the degree of strategic response χ is always positive. If others acquire less information and become less aggressive, there are incentives to look for information and step in to replace them. However, these forces only partially offset the initial change, $\chi < \infty$. In particular, costs to adjust information limit the ability to react and result in lower χ. Formally, we show in Appendix B.5 that χ is decreasing in the curvature of the information cost function.[28]

3.2 Bounded rationality

Strategic interactions between investors rely on their understanding of market structure. For example, in the rational expectations equilibrium of Section 3.1, each investor knows the strategies followed by everyone else. Practically, how would investors figure out other people's strategies? Both in our model and in the theories described above, investors only need to know the aggregate elasticity $\mathcal{E}_{agg}$, but not the actions of each of the other investors. In the real world, institutions can track changes in investment styles directly (e.g. industries, factors, arrival of activist investors) or through their impact on prices (e.g. price impact, volatility, price informativeness). While this information is useful, it is still a leap to assume investors can follow exactly the optimal policies

[27] The relation between $\mathcal{E}_i$ and $\mathcal{E}_{agg}$ is not linear in general. In Appendix B.4 we find a two-parameter family of simple cost functions under which this relation is exactly linear as in equation (4). Each of the two parameters maps in closed-form to the degree of strategic response χ and individual elasticity $\underline{\mathcal{E}}_{0,i}$.

[28] Coles et al. (2022) show a full degree of strategic substitution in the baseline setup of Grossman and Stiglitz (1980) without adjustment costs.

in frictionless models.

First, the information available to investors about the aggregate elasticity might be imperfect.[29] In such a setting the response to other investors is dampenened. For example, assume an investor wants to react to aggregate elasticity with a coefficient χ_0, but she only observes a noisy signal about $\mathcal{E}_{agg}$. Then, her elasticity choice can be written as

$$\mathcal{E}_i = \underline{\mathcal{E}}_i - \chi_0 \theta \cdot \mathcal{E}_{agg} + \epsilon. \tag{10}$$

Because the investor cannot separate the noise from the information about $\mathcal{E}_{agg}$, she responds to her signal with a Bayesian shrinkage factor $0 < \theta < 1$. The residual ϵ is due to the noise in the signal. Appendix C.4 provides derivations and explicit expressions for these quantities. The effective degree of strategic response is $\chi_0\theta$ and incorporates the baseline strategic response χ_0 with the dampening factor θ.

Second, investors have to be sophisticated enough to understand their strategy should react to what other investors are doing. A recent strand of research considers equilibria in which investors miss the actions of others (Eyster and Rabin (2005), Greenwood and Hanson (2014), Eyster et al. (2019), Bastianello and Fontanier (2021)).[30] Neglecting equilibrium forces can either amplify or mitigate the degree of strategic response. On the one hand, investors could simply ignore how the elasticity choice of others affect their investment opportunities. In this case, we will not observe any strategic response. On the other hand, investors might understand the direct effect of changes in elasticity but fail to realize that others react to those as well, a form of partial equilibrium thinking as in Bastianello and Fontanier (2021). For example, all investors understand there is a rise in passive investing but fail to realize that others will react by trading more aggressively. We include partial equilibrium thinking into the calculation from Section 2.3 on the effect of a rise in

[29]Imperfect information about other investors' strategies is different from imperfect information about fundamentals or noise traders.

[30]The neglect of actions by others is relevant beyond financial markets. For example, Angeletos and Lian (2018), Farhi and Werning (2019), and Gabaix (2020) show it has profound implications for monetary and fiscal policy.

passive investing. We show in Appendix C.5 that the new aggregate elasticity becomes

$$\mathcal{E}_{NEW}^{PET} = \alpha\mathcal{E}_0 + (1-\alpha)\chi\alpha\mathcal{E}_0. \tag{11}$$

Because investors do not account for the response of others, they overreact to the initial change in elasticity. With partial equilibrium thinking, the strategic response is stronger than in the baseline (see equation (5)) by a factor $1 + \alpha\chi$. This leads to a relatively higher final level of aggregate elasticity, bringing the economy closer to the idealized view of financial markets.

3.3 Strategic complementarities

Finally, some forces generate strategic complementarity rather than substitutability, which yields negative values of the parameter χ. In these situations, when some investors become less aggressive, other investors also pull out of markets instead of replacing them.

One such case arises when investors worry about the price impact of their trades. In Appendix Section C.3, we show that a model of market power in the style of Kyle (1989) yields a negative value of χ.[31] Specifically, the standard CARA elasticity becomes

$$\mathcal{E}_i = \frac{1}{\rho_i\sigma^2 + \underbrace{(\mathcal{E}_{agg} - \mathcal{E}_i)^{-1}}_{\lambda_{-i}}}. \tag{12}$$

The investor responds to the price based on her risk aversion and the risk of the asset, $\rho_i\sigma^2$, and the slope of the residual demand curve for the asset, what Kyle (1989) calls λ_{-i}. When other investors are more price elastic, it enhances liquidity in the market. In turn, this facilitates my ability to trade and I can be more responsive to prices. This type of complementarity holds in a broader family of theories of liquidity such as Vayanos and Wang (2007).[32]

Strategic complementarities can also arise through social interactions. When investors follow their peers, as in Hong et al. (2004), changes in some investors are amplified by similar decisions

[31] We also show that the measure of price impact Kyle's λ is closely related to the inverse of aggregate elasticity.
[32] Rostek and Yoon (2023) review models of price impact.

from other investors.[33] If I see others around me trade a stock more aggressively, I also want to trade that stock more aggressively. This herding leads to negative values of χ.

4 Estimating the Degree of Strategic Response

In this section, we estimate the degree of strategic response χ and demand elasticities in the context of the U.S. stock market. First, we enrich our model to account for the heterogeneity of stocks and investors. Then, we design and implement a new identification strategy for demand estimation in the presence of strategic interactions.

4.1 Quantitative model

Individual decisions. In practice, agents invest in many assets. Therefore, an empirical model must make sure that portfolio positions add up to total assets for each investor. In addition, it should also account for the portfolio aspect of financial decisions, that is, substitution across assets. Koijen and Yogo (2019) show that a logit framework satisfies both of these requirements. We denote each security by the index k, the total assets of an investor by A_i, and the portfolio share of investor i in security k by w_{ik}. Therefore $d_{ik} = \log(w_{ik}A_i) - p_k$. The framework of Koijen and Yogo (2019) corresponds to specifying a log-linear model for relative portfolio shares w_{ik}/w_{i0} instead of the individual demand directly, with index 0 being the outside asset.[34] We follow this approach. For each investor, we take as given total assets under management, A_i, and the investment universe, $\mathcal{K}_i$, that is, the set of assets they can invest in.

Second, we need to specify the baseline levels of demand and elasticity $\underline{d}_i$ and $\underline{\mathcal{E}}_i$. We assume that each of those combines potentially distinct sets of asset characteristics using investor-specific coefficients. Going back to the setting of Section 3, an interpretation of this assumption is that investors form priors on different assets based on their characteristics; for example, characteristics could capture factor loadings. This corresponds to expressing the baseline demand as $\underline{d}_{ik} = \underline{d}_{0i} + \underline{d}'_{1i}X_k + \epsilon_{ik}$ and the baseline elasticity as $\underline{\mathcal{E}}_{ik} = \underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i}X_k$, where X_k is the vector of

[33] Hirshleifer (2020) more broadly emphasizes the importance of social interactions in finance.
[34] Appendix D.4 details the empirical definition of the outside asset.

characteristics. We also account for unobservable asset-specific changes in demand by including a shock ϵ_{ik} in $\underline{d}_{ik}$. For example, this shock captures the private signal η and noise trading x of the model of Section 3.

Third, the elasticity of demand controls not only how demand responds to the price p_k, but also to the reference price $\bar{p}_k$. We assume that the reference price is a function of the characteristics X_k. The product of this component with the baseline elasticity $\underline{\mathcal{E}}_{ik}$ yields terms that are only functions of characteristics, and are therefore absorbed in $\underline{d}_{ik}$. However, the multiplication with the strategic response $\chi\mathcal{E}_{agg,k}$ yields two additional terms: a linear loading on $\mathcal{E}_{agg,k}$ and an interaction of $\mathcal{E}_{agg,k}$ with the characteristics X_k. We parametrize these terms by the coefficients ξ and ζ, respectively.

Finally, we let demand parameters and all equilibrium quantities change over time, making the estimation focused on information from the cross-section of stocks. Specifically, we allow all quantities and parameters of the model to depend on time, except (χ, ξ, ζ). For ease of notation we drop the subscript t except when ambiguous in the remainder of the paper. Putting it all together, our model of portfolio demand is[35]

$$\log \frac{w_{ikt}}{w_{i0t}} - p_{kt} = \underline{d}_{0it} + \underline{d}'_{1it} X_{kt} - \mathcal{E}_{ikt}\ p_{kt} + \xi \mathcal{E}_{agg,kt} + \zeta' \mathcal{E}_{agg,kt} X_{kt} + \epsilon_{ikt}, \tag{13}$$

$$\mathcal{E}_{ikt} = \underline{\mathcal{E}}_{0it} + \underline{\mathcal{E}}'_{1it} X_{kt} - \chi\ \mathcal{E}_{agg,kt}. \tag{14}$$

Starting from the relative shares $\vartheta_{ik} = w_{ik}/w_{i0}$, the actual shares can be obtained by

$$w_{ik} = \frac{\vartheta_{ik}}{1 + \sum_{k \in \mathcal{K}_i} \vartheta_{ik}}, \tag{15}$$

$$w_{i0} = \frac{1}{1 + \sum_{k \in \mathcal{K}_i} \vartheta_{ik}}. \tag{16}$$

Interestingly, the demand system of Koijen and Yogo (2019) is a special case of this framework. In their model, demand elasticities are fixed structural parameters.[36] This corresponds to setting $\underline{\mathcal{E}}_{1i} = 0$ and $\chi = \xi = \zeta = 0$. Therefore, their model implicitly assumes no strategic response.

[35] To match equation (13) with equation (1), recall that: $d_{ik} = \log \frac{A_i w_{ik}}{P_k}$.

[36] Technically, in the logit model the demand elasticity is $1 - (1 - w_{ik})(1 - \mathcal{E}_{ik})$. For values of w_{ik} that are small relative to one, as in the data, this expression is close to $\mathcal{E}_{ik}$. Hence we refer to $\mathcal{E}_{ik}$ as the demand elasticity throughout the paper.

Consequently, when some investors are removed from the markets, the other ones do not step in with larger elasticities. This is the polar opposite from the common view of "fiercely competitive financial markets," which corresponds to $\chi \to \infty$. Our framework lets us quantify how close or far reality is from these two extremes.

Passive investors. We account separately for passive investors. By passive, we mean that these are investors whose demand does not respond to prices. Index funds are a specific example of such investors. Our notion is broader though, because it accommodates arbitrary fixed portfolios. To represent such behavior, we simply replace equation (14) by $\mathcal{E}_{ik} = 0$.[37] Separating out these investors is important, not only because of their low level of elasticity, but also because they do not respond to aggregate trading conditions. We denote the set of active investors for asset k by $Active_k$ and the fraction of asset k held by this group of investors as $|Active_k|$.

Equilibrium prices and elasticities. Going from individual decisions to an equilibrium relies on market clearing. As in the model of Section 2, two equilibrium objects play a role in individual decisions: prices, p_k, and aggregate elasticities, $\mathcal{E}_{agg,k}$. The corresponding equilibrium conditions are

$$\sum_i w_{ik} A_i = P_k, \ \forall k, \tag{17}$$

$$\sum_i \frac{w_{ik} A_i}{P_k} \mathcal{E}_{ik} = \mathcal{E}_{agg,k}, \ \forall k. \tag{18}$$

We normalize the number of shares available to 1 to obtain the market-clearing condition for assets, equation (17). Said otherwise, p_k denotes the log market capitalization.

[37] Importantly, the elasticity that we measure is for individual stocks, that is to the relative price of different stocks. It is possible that passive institutions contribute to the elasticity of the aggregate demand for stocks. Neither our model, nor any other empirical model to our knowledge, accomodates simultaneously these different levels of aggregation.

4.2 Data

We estimate the model for the U.S. stock market. We obtain stock-level data from CRSP: price, dividends, and shares outstanding. We merge the CRSP monthly stock file with COMPUSTAT for balance sheet information and compute additional stock-level characteristics: book equity, operating profitability, and net investment rate.

We use log book equity, profitability, investment, and the dividend yield (total dividends divided by book equity) to construct the vector of characteristics. We transform these variables so that they follow normal distributions because this better captures the nonlinearity of their relation with valuations than raw values.[38] To this set of variables, we add the square of the normalized book equity to form X_k. Furthermore, for the sake of tractability, our baseline analysis only includes book equity in the determination of the individual elasticity and the reference price. That is, we restrict $\underline{\mathcal{E}}_{1i}$ and ζ to be equal to 0 on all dimensions but book equity.

We obtain portfolio holdings data from the 13F filings to the SEC from 2001 to 2020. We build the dataset from the SEC EDGAR website following the method of Backus et al. (2019, 2020). The SEC requires that every institution with more than \$100m of assets under management files a quarterly report of their stock positions. We find that collectively the holdings reported in the 13F filings account for 80% of the total stock market capitalization. We follow Koijen and Yogo (2019) to construct the final panel dataset. Like them, we define the investment universe of an institution as the set of stocks it holds at any point between the current date and 3 years before.

Section 5.2 studies the impact of varying these implementation choices. Appendix D provides additional details on data construction.

4.3 Identification Strategy

To estimate the model described above we have to overcome three difficulties: (i) a reflection problem induced by the interactions between investors; (ii) the classic problem of endogeneity in demand estimation; and (iii) how to implement the estimation given that one of the "regressors,"

[38]This procedure is analogous to the widespread practice in empirical asset pricing (e.g., Fama and French (1992)) of using quantiles of characteristics instead of their values.

the aggregate elasticity, is unknown. We explain our identification strategy, starting from an ideal experiment, and progressively introducing the challenges brought on by the real world.

4.3.1 The reflection problem

In our setting, individual investor elasticities $\mathcal{E}_{ik}$ depend on an investor-specific term, $\underline{\mathcal{E}}_{ik}$, and on the aggregate elasticity $\mathcal{E}_{agg,k}$:

$$\mathcal{E}_{ik} = \underline{\mathcal{E}}_{ik} - \chi \mathcal{E}_{agg,k}. \tag{19}$$

We need to disentangle whether investors are elastic because of their own characteristics or in response to other investors in the market. For example, if in a market we see that all investors behave in a very elastic manner, it could be that each of them is fundamentally very elastic, high $\underline{\mathcal{E}}_{ik}$. But it could also be the consequence of a strong positive feedback where $\chi < 0$. This identification problem is the reflection problem (Manski, 1993): are individual actions the fruit of individual traits or a reflection of the behavior of others?

The ideal experiment to answer this question would be to see two parallel worlds where the same investor faces different trading counterparts of known fixed elasticities for the same stock. Then, we would estimate the relation between the elasticity of this investor and the elasticity of the investors she is facing.

The real world provides us with a closely related situation: the same investor trades multiple stocks, each with a different mix of investors. Even assuming that investors are exogenously allocated and stocks are identical (so that $\underline{\mathcal{E}}_{ik} = \underline{\mathcal{E}}_{i}$), this is not quite the same as the ideal experiment. There is a chicken-and-egg problem: to estimate one investor's elasticity decisions, we need to already know how the other investors choose their elasticities. Figure 1 illustrates this idea: we need to compare how Barbora trades differently when facing different groups of other investors, such as for GameStop and Tesla. To do so, we simultaneously need to figure out the elasticity for Isabeau, Cléo, Kelsey, etc. In particular, these investors' elasticities likely respond to others' elasticities, including Barbora's.

The following theorem shows conditions under which we can back out the degree of strategic

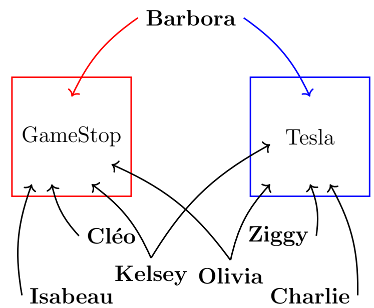

Figure 1. Illustration of identification strategy.

response from individual observations of demand elasticities. For simplicity, we focus on the case of constant individual-specific components $\underline{\mathcal{E}}_{ik} = \underline{\mathcal{E}}_i$.

Theorem 1. *A decomposition of demand elasticities* $\{\mathcal{E}_{ik}\}_{i,k}$ *into individual elasticities* $\{\underline{\mathcal{E}}_i\}_i$ *and the degree of strategic response* χ *is unique if:*

(a) The graph $\mathcal{G}$ *of investor-stock connections is connected.*

(b) Position-weighted averages of demand elasticities are not constant across stocks: there exists k *and* k' *such that* $\sum_{i \in I_k} \frac{w_{ik}}{P_k} A_i \underline{\mathcal{E}}_i \neq \sum_{i \in I_{k'}} \frac{w_{ik'}}{P_{k'}} A_i \underline{\mathcal{E}}_i$.

Intuitively, this result states that if there is enough mixing in the allocation of investors to stocks, we can recover χ. For example, if investors are isolated (violating part (a)), or if in aggregate the composition of demand for each stock is the same (violating part (b)), it is not possible to escape the reflection problem. We derive and discuss this theorem in more depth in Appendix E.2. In particular, we explain that the two conditions for the result to apply are satisfied in our setting.

While this result explains how we can separate individual components of elasticities from strategic responses, it leaves aside some other challenges to identification. First, the same investor can behave differently for different stocks, that is $\underline{\mathcal{E}}_{ik}$ varies across stocks k within i. For example, the investor might trade differently small and large stocks, irrespective of who the other investors are in these stocks. Our model incorporates variation in individual elasticity across stocks conditional on observable characteristics of these stocks — the characteristics X_k in equation (14). Theorem 1 still applies conditional on these characteristics.

Second, the demand of investors for various stocks also depends on the residual ϵ_{ik} (equation (13)), which are typically correlated across investors. Said otherwise, similar unobserved common determinants of demand affect different investors. Because elasticities are estimated from data on demand, these correlated residuals could contaminate the estimation of the degree of strategic response. Outside of our model, a related issue would arise if the individual elasticity varied due to unobserved sources of variations correlated across investors.[39] To overcome these challenges, one needs to compare situations where differences in aggregate elasticity $\mathcal{E}_{agg}$ are the result of exogenous variation in the allocation of investors. We propose using instrumental variables that are plausibly exogenous to investor demand. This is the same issue as basic demand estimation, in which the price p_k is correlated with residual demand ϵ_{ik}. The next section presents this approach and discusses the specific instruments of our implementation.

4.3.2 Instrumental variables

To understand better why instruments are crucial to the estimation, assume for a moment that the aggregate elasticity for each stock, $\mathcal{E}_{agg,k}$, is measured in our data.[40] Then, by combining equation (13) and (14), the model is a standard linear regression equation:

$$\log \frac{w_{ik}}{w_{i0}} - p_k = \underline{d}_{0i} + \underline{d}'_{1it} X_k - \left(\underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k - \chi \ \mathcal{E}_{agg,k}\right) \ p_k + \xi \mathcal{E}_{agg,k} + \zeta' \mathcal{E}_{agg,k} X_k + \epsilon_{ik}. \tag{20}$$

The parameters are $\underline{d}_{0i}$, $\underline{d}_{1i}$, $\underline{\mathcal{E}}_{0i}$, $\underline{\mathcal{E}}_{1i}$, and (χ, ξ, ζ). Challenges to identification come down to the correlation of the residual demand ϵ_{ik} and the regressors, in particular the equilibrium objects p_k and $\mathcal{E}_{agg,k}$.

The simplest possible identifying assumption takes residual demand as exogenous to all other variables to get the moment condition

$$\mathbf{E}\left[\epsilon_{ik} | X_k, p_k, \mathcal{E}_{agg,k}\right] = 0. \tag{21}$$

[39]This would correspond to changing equation (14) to $\mathcal{E}_{ik} = \underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k - \chi \ \mathcal{E}_{agg,k} + \nu_{ik}$. with ν_{ik} correlated across investors. While the instruments we use would overcome the identification problem from these residuals, we do not include such residuals in the model because the estimation becomes numerically intractable.

[40]The discussion of the previous section explains how to deal with the elasticity equilibrium. We come back to this in our discussion of how to implement the estimation altogether.

Then, we could estimate (20) using ordinary least squares. The independence of ϵ_{ik} from X_k is naturally motivated by taking the supply of assets as exogenous, as in endowment economies (Lucas, 1978). Furthermore, the independence from p_k and $\mathcal{E}_{agg,k}$ relies on the logic that residual demands do not matter for equilibrium outcomes because they "cancel out" in the aggregate. This rules out both the presence of non-atomistic investors and correlated demand shocks. Both of these last assumptions are not likely to hold for institutional investors. For example, there could be a fad where a large group of investors are enthusiastic about a specific stock, meaning a high ϵ_{ik} for this stock. This increase in demand would push the price p_k higher — see the equilibrium conditions in equations (17) and (18). This would generate a positive correlation between p_k and ϵ_{ik} which leads to a downward bias in estimates of elasticity.

Because the simple identifying assumption is not plausible, we relax it and propose an alternative identification strategy. We look for sources of variation in the aggregate variables that are orthogonal to the residual demand. Specifically, using instruments $(\hat{p}_k, \hat{\mathcal{E}}_{agg,k})$ for the aggregate variables $(p_k, \mathcal{E}_{agg,k})$ allows us to weaken the moment condition (21) to

$$\mathbf{E}\left[\epsilon_{ik}|X_k, \hat{p}_{i,k}, \hat{\mathcal{E}}_{agg,k}\right] = 0. \tag{22}$$

Provided that our instruments are relevant, we could estimate the model using two-stage least squares — again, assuming that $\mathcal{E}_{agg,k}$ is known.

To construct these instruments, we use variation in total assets and the investment universe of institutions, an approach introduced by Koijen and Yogo (2019). The instrument for the price of asset k follows

$$\hat{p}_{k,i} = \log\left(\sum_{j \neq i} A_j \frac{\mathbf{1}_{k \in \mathcal{K}_j}}{|\mathcal{K}_j|}\right), \tag{23}$$

where $\mathbf{1}_{k \in \mathcal{K}_j}$ is an indicator variable of when stock k is in investor j investment universe. This instrument corresponds to how much money would flow to stock k if all investors other than i had an equal-weighted portfolio.For example, a stock with large investors has more money flowing towards it. Given our assumption of downward-sloping demand for stocks, a larger exogenous demand generates higher prices that are uncorrelated with residual demand.

In addition to the price of each asset, our setting includes another equilibrium variable, the aggregate elasticity $\mathcal{E}_{agg,k}$, for which we develop a new instrument:

$$\hat{\mathcal{E}}_{agg,k} = \frac{1}{1+\chi|\widehat{Active_k}|} \frac{\sum_{j \in Active_k} A_j/|\mathcal{K}_j| \cdot \mathbf{1}_{k\in\mathcal{K}_j} \cdot \underline{\mathcal{E}}_{jk}}{\sum_j A_j/|\mathcal{K}_j| \cdot \mathbf{1}_{k\in\mathcal{K}_j}}. \tag{24}$$

The instrument is the solution to the elasticity equilibrium defined by equations (14) and (18), where we have replaced the endogenous weights w_{ik} with counterfactual weights under the assumption that each investor holds an equal-weighted portfolio.[41] The variation in this instrument also comes from variation across investors' investment universes. However, the asset flows are weighted by individual elasticity: a stock with more intrinsically inelastic investors (for example, passive mutual funds) will tend to have a lower aggregate elasticity. The degree of strategic response χ is the response of asset demand to the interaction of aggregate elasticity with the price (see equation (20)).

The instrument $\hat{\mathcal{E}}_{agg,k}$ depends on the model parameters ($\underline{\mathcal{E}}_{0i}$ and $\underline{\mathcal{E}}_{1i}$). This is not an issue for identification as parameters are by definition not endogenous. However, this precludes us from using standard methods such as two-stage least squares to estimate the model; anyways, the elasticity equilibrium already prevents us from using these standard methods. As part of the estimation, we look for a fixed point in which the estimated values of $\underline{\mathcal{E}}_{jk}$ coincide with those for the construction of the instrument in equation (24).[42]

Why is it plausible that these instruments satisfy the identifying restriction in the moment condition equation (22)? For both instruments, it is sufficient to assume that the variation in total assets and the investment universe is exogenous to the residual demand, an assumption shared

[41]Our instrument for aggregate elasticity is the solution to the following problem:

$$\hat{\mathcal{E}}_{ik} = \underline{\mathcal{E}}_{ik} - \chi\, \hat{\mathcal{E}}_{agg,k}; \qquad \sum_j \hat{w}_{jk}[A_j/\exp(\hat{p}_k)]\hat{\mathcal{E}}_{jk} = \hat{\mathcal{E}}_{agg,k},$$

where the counterfactual weights $\hat{w}_{jk}$ are defined as:

$$\hat{w}_{jk} = \frac{\mathbf{1}_{k\in\mathcal{K}_j}}{|\mathcal{K}_j|}.$$

[42]Appendix Section E.3 explains how we construct the initial guess from a model without strategic interactions.

with Koijen and Yogo (2019). The investment universe is often determined by mandates, which are predetermined rules on which assets can be held. To the extent that investment universes are determined by mandates — predetermined rules on which assets can be held — correlated shifts in demand such as fads do not affect them. Section 5.2 discusses threats to these identification assumptions and implements diagnostics to assess their importance.

Appendix Section E.1 lists the unconditional moments derived from condition (22) that we use for estimation. In Section 4.3.3, we detail our numerical procedure for estimating the model.

Relevance condition. To evaluate the strength of our instruments, we run what would be a first-stage regression in a standard two-stage least square estimation. First, we regress the price onto the instrument and the other characteristics for each manager. For each date, we compute the first and the fifth percentile of the Kleibergen and Paap (2006) F-statistics across managers. Figure 2 reports the histogram of these percentiles across all dates. At least 95% of the F-statistics in any given date are above 18 (panel A); panel B reports the first percentile. We also confirm the relevance of the elasticity instrument. In the panel, we regress the product of the price interacted with the aggregate elasticity onto their instrumented version and the other characteristics. We represent the histogram of the F-statistic of this regression for each date in panel C; the F-statistic is always above 10. Moreover, we find that the F-statistic of a pooled first-stage regression of the aggregate elasticity and its interactions with price and book equity onto their instruments is greater than 100.

4.3.3 Implementation

Last, we need to implement the estimation free of the identification issues discussed above. We cannot estimate (20) using off-the-shelf methods. This is because the degree of strategic response χ and the aggregate elasticities $\mathcal{E}_{agg,k}$ must not only satisfy moment conditions but also respect the two-layer equilibrium relations. A naïve approach to solve all these conditions simultaneously is computationally untractable due to the large dimension of the parameter space.

However, we develop an algorithm that leads to rapid computation. The basic idea of our method is to focus on two nested equilibrium questions. On the one hand, if one knows the

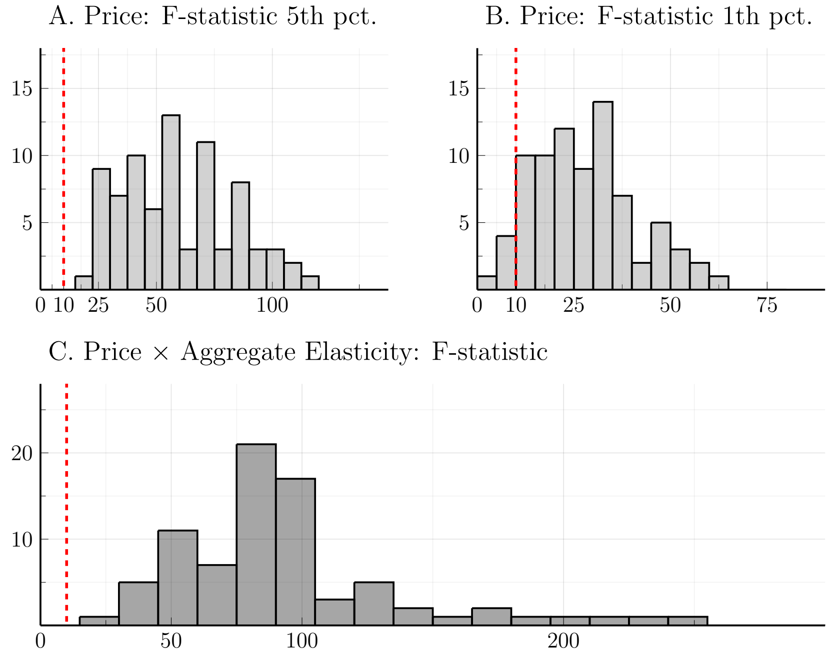

Figure 2. Relevance condition for the price and elasticity instruments.
Figure 2 shows the F-statistic of the first-stage regression for the price and aggregate elasticity variables. For the price, we estimate the F-statistic (Kleibergen-Paap) at the manager level for each year. We summarize these statistics at every date with the 5th percentile (Panel A) and 1st percentile (Panel B). The vertical red dashed line indicates the critical value of 10. In Panel C, we regress the elasticity interacted with the price onto their instrumented version and report the F-statistic for each date. The sample period is 2001–2020.

coefficient on aggregate elasticity, solving the values of aggregate elasticities can be done using an iteration process: run standard instrumental regressions at the investor-date level to estimate their demand, then update aggregate elasticities using equation (18); repeat until obtaining convergence. On the other hand, if one knows the equilibrium quantities, finding the coefficient on the interaction of prices and aggregate elasticities involves a single large panel regression. Put together, finding a set of elasticity estimates and the parameters for strategic interactions (χ, ξ, ζ) that are internally consistent with one another corresponds to a low-dimensional fixed-point problem that we solve using the standard Newton method. Appendix Section E.3 details this estimation procedure.

5 Estimates

5.1 Degree of strategic response χ

The first row of Table 2 reports our baseline estimates. The estimated value of the degree of strategic response is $\chi = 2.97$. We construct GMM standard errors for this estimate that account for the equilibrium feature of our demand model — Appendix F details this procedure. With a standard error of 0.47, the parameter χ is precisely estimated.

A degree of strategic response of 2.97 implies substantial reactions at the individual level. If all other investors become more aggressive and increase their elasticity by 1, an atomistic investor would respond by decreasing her elasticity by 2.97. However, this estimate of χ points to an equilibrium behavior far from both the common view of $\chi \to +\infty$ and the no-strategic-response benchmark of $\chi = 0$. For example, our simple calculation in equation (5) shows that we need large values of χ for strong equilibrium effects. Making 50% of investors passive, a value of χ of at least 18 is necessary to compensate 90% of the drop in aggregate elasticity. This is an order of magnitude larger than our main estimate of 2.97, and actually than all of our estimates. Going back to the theories of Section 3, a positive value for χ suggests that theories based on strategic substitution (e.g. models of information acquisition as in Grossman and Stiglitz (1980)) better explain the data than those featuring complementarity (e.g. models of market power as in Kyle (1989)). Furthermore, the low value of χ suggests the presence of significant frictions impeding investor reaction. We investigate the quantitative implications of our value of χ for the impact of the rise of passive investing in Section 6.

Table 2 also reports the coefficient ζ, which captures the flipside of χ: how much changes in the aggregate elasticity affect the response to the reference value of the price $\bar{p}_k$, mediated by stock characteristics. Consistent with the model of Section 2, this coefficient takes the opposite sign from χ: investors respond to the deviation from the benchmark price.[43] The estimated value of -0.48 is statistically significant.

[43]Recall that the characteristic for this value is book equity, hence larger values of X_k correspond to larger values of $\bar{p}_k$.

5.2 Threats to identification

We consider potential threats to our identification strategy. To do so, we design variations of our baseline specification to detect whether these threats affect our estimation. Table 2 reports the results of the estimation for these alternative specifications in rows 2 to 14. Overall, the estimates of competition χ do not vary substantially across specifications — all but one value are within one standard error (0.47) of our baseline estimate — and are consistently statistically significant, with the exception of rows 8 and 13. The estimates of ζ are all negative, with all but one value between -0.3 to -0.8, and all rows except 10, 13 and 14 being statistically significant.

First, recall that our instruments depend on AUM (see equations (23) and (24)), hence they are valid if variation in AUM is exogenous. This assumption is violated if flows into institutions respond to shocks that are correlated with asset demand. Consistent with this view, Sirri and Tufano (1998) and Chevalier and Ellison (1997) show that mutual fund flows follow fund performance. While such behavior might bias our estimates, two elements suggest its importance is likely to be limited. First, flow-performance sensitivity only explains a small fraction of the variation in fund flows. Second, each individual stock only contributes modestly to the overall performance of a fund. Still, we assess whether endogenous flows affect our conclusions. To do so, we replace current AUM by its lagged value for each institution in the construction of the instruments. Rows 2 and 3 report the estimates using a one-year or a two-year lag and find values of χ of 2.71 and 2.71, a small deviation from our baseline estimate, both statistically and economically.

The second ingredient of our instruments is the investment universe of each investor. We compute these sets over a long interval of 3 years to ensure that they are not sensitive to transitory shifts in demand. The key assumption is that investment universes are strongly persistent. Appendix Table IA.1 measures their evolution over time and finds support for this assumption. Still, one could worry about persistent demand shocks yielding slow changes in the investment universe. Rows 3 and 4 shrink and expand the window for estimating the universes by one year. These variations yield values of χ very close to our baseline.

Our estimation accounts for the fact that investors look at diverse signals when evaluating stocks by including multiple firm characteristics. However, for the sake of tractability, the baseline

Table 2.
Estimates of the degree of strategic response χ under alternative specifications

	Estimates for χ		Estimates for ζ	
	Estimate	s.e.	Estimate	s.e.
(1) Baseline Specification	2.97	0.47	−0.48	0.14
(2) Instruments using 1yr-lagged AUM	2.71	0.49	−0.41	0.16
(3) Instruments using 2yr-lagged AUM	2.71	0.30	−0.47	0.13
(4) Instruments using 2yr investment universe	3.23	0.30	−0.54	0.24
(5) Instruments using 4yr investment universe	2.80	0.69	−0.44	0.15
(6) Additional fundamental: book equity squared	2.84	0.33	−0.55	0.14
(7) Additional fundamental: profitability	3.27	0.13	−0.80	0.22
(8) Additional fundamental: investment	3.06	1.56	−0.52	0.16
(9) Additional fundamental: dividend yield	3.01	0.35	−0.56	0.14
(10) AUM-weighted estimation	2.53	0.25	−0.33	0.26
(11) Book AUM-weighted estimation	2.65	0.41	−0.40	0.12
(12) Alternative characteristic normalization	3.01	0.30	−1.46	0.23
(13) Investor-type grouping	3.14	2.52	−0.46	0.33
(14) BE-weighted instrument for $\mathcal{E}_{agg}$	2.30	0.75	−0.31	0.44
(15) No instrument for $\mathcal{E}_{agg}$	0.04	0.22	0.47	0.06
(16) No instruments	0.63	0.29	0.47	0.16

Table 2 presents statistics of estimates of χ across dates (2001Q1–2020Q4) under various specifications. Our baseline specification (1) estimates the model:

$$\log \frac{w_{ikt}}{w_{i0t}} - p_{kt} = \underline{d}_{0it} + \underline{d}_{1it}' X_{kt} - \left(\underline{\mathcal{E}}_{0it} + \underline{\mathcal{E}}_{1it}' X_{kt} - \chi\ \mathcal{E}_{agg,kt}\right)\ p_{kt} + \xi \mathcal{E}_{agg,kt} + \zeta' \mathcal{E}_{agg,kt} X_{kt} + \epsilon_{ik}, \qquad (25)$$

where X_{kt} contains log book equity and log book equity squared, profitability, investment, and dividend yield, and $\underline{\mathcal{E}}_{1it}$ and ζ are restricted to only load on log book equity. Active investors with fewer than 1,000 stock holdings are pooled together based on their assets under management, such that each group on average contains 2,000 stock holdings. Observations are weighted such that each date receives equal weight, and within each date, each investor group's weights sum to the same constant. Specifications (2) and (3) use a one-year and two-year lag for institutions' AUM (A_j in equations (23) and (24)) in the construction of the instruments. Specifications (4) and (5) vary the empirical definition of an institution's investment universe by reducing and extending the look-back period for investment-universe construction by one year. Specifications (6) to (9) add interactions between the aggregate elasticity $\mathcal{E}_{agg}$ and the characteristics book equity squared, operating profitability, investment and dividend yield. That is, restrictions on interactions in ζ' are relaxed one at a time. Specification (10) weighs observations within date by each investors' AUM. Specification (11) similarly weighs observations by the book value of assets under management. Specification (12) uses an alternative normalization of stock characteristics by projecting log market equity onto stock characteristics via polynomial regressions in the cross-section of stocks. Specification (13) groups investors both by investor type and AUM. Institutional investors whose type we cannot determine are bundled together in a separate group. Specification (14) shows estimates of χ based on a book-equity weighted instrument. Specification (15) reports results without instrumenting for the aggregate elasticity $\mathcal{E}_{agg}$. Specification (16) additionally removes the instrument for prices. GMM standard errors clustered by institution and stock are computed as described in Appendix F.

specification only interacts aggregate elasticity with book equity to estimate the parameter ζ. To evaluate whether this simplification is consequential for the estimation, we include interactions of aggregate elasticity with each of the other characteristics in X_k one by one in rows 6 to 9. These additional terms do not lead to substantial changes in the estimated χ; with the only noticeable change of a less precise estimate in row 8.

One limitation of our framework is that it assumes that all investors react to the aggregate elasticity in the same way: χ is constant across investors. Appendix A.4 shows that in a setting with heterogeneous degrees of strategic response, what matters for the rise in passive investing is heterogeneity in χ related to investor size. In our baseline estimation, all investors contribute equally to the estimate of χ. In row 10, we weigh observations proportionally to their assets under management with a maximum weight of 5%. Row 11 repeats the same exercise using AUM computed using book values. If our model was misspecified and the competitive response varied by investor size, this different specification would lead to different estimates. This is not the case here, with close estimates to our baseline, suggesting that we capture the empirically relevant moment for the rise in passive investing.

We then consider variation in some of the details of the implementation. In row 12, instead of normalizing book equity to follow a normal distribution, we first estimate a regression of log market capitalization on log book equity and its square to estimate the shape of the non-linear relation between these variables — note that this ancillary regression could create some endogeneity because it uses p_k. This alternative approach leads to a tiny change in estimated value. In the baseline, active investors with fewer than 1,000 stock holdings are grouped together based on their assets under management such that each group on average contains 2,000 stock holdings.[44] A finer way to construct these groups is to make them based on investor types, but data coverage is incomplete. The estimates in row 13 updates our estimation based on these data, which results in little change in point estimate but large standard errors. Finally, row 14 considers an alternative construction of the instrument where the counterfactual portfolio positions are weighted by book equity instead of being equally weighted. While these weights are potentially more realistic and can strengthen the relevance condition, their ad-hoc nature might weaken the plausibility of the exogeneity condition. This leads to an estimated χ of 2.30, the furthest specification to our baseline but only a less than 25% reduction in the estimate.

[44] This grouping ensures enough observations for each group to avoid incidental parameter issues.

Finally, we also estimate the model without using instruments. Row 15 removes the instrument for aggregate elasticity. In this case, we find an average value of χ of 0.04 and ζ becomes positive at 0.47. These estimates, far away from any other specification, confirm that it is important to account for the endogeneity of elasticities — because they depend on actual portfolio weights, which themselves depend on residual demand. Also removing the instruments for prices — row 16 — still leads to strong deviations in the estimates, reinforcing this conclusion.

5.3 Stock-level elasticities

The model delivers estimates of aggregate elasticity, $\mathcal{E}_{agg,k}$, for each stock. Figure 3 represents these elasticities as a function of stock market capitalization for 2011Q3. Each green dot corresponds to an elasticity estimate of one stock in our model for that date. We compare our estimates to a model where individual-level elasticities are fixed, that is, where $\underline{\mathcal{E}}_{1,i} = 0$ and $\chi = \xi = \zeta = 0$. These estimates are represented by red squares.

There is substantial cross-sectional variation in elasticities, lending credence to our ability to identify the degree of strategic response χ. In both sets of estimates, the demand curve for individual stocks is inelastic with average values around 0.4. This magnitude is far from the asset-pricing benchmark of perfectly horizontal demand curves with infinite elasticity.[45] However, it is consistent with other empirical estimates, in particular based on portfolio data; see for example the discussion in Chang et al. (2014) and Koijen and Yogo (2019).

Figure 3 demonstrates a few ways in which accounting for the endogeneity of demand elasticities is important. First, the full model estimates exhibit less variation than the model with constant elasticities. With constant individual elasticities, variation in investor composition directly translates into variation in aggregate elasticities. However, with a positive degree of strategic response χ, investors react to each other and soften such variation. For example, if an active investor with high elasticity takes a position in a stock, other investors respond by trading less aggressively. Thus, stocks become more similar to each other.

Second, the full model exhibits a stronger negative relation between the size of a stock and

[45] Petajisto (2009) shows that standard models with risk aversion and many assets also imply very large elasticities.

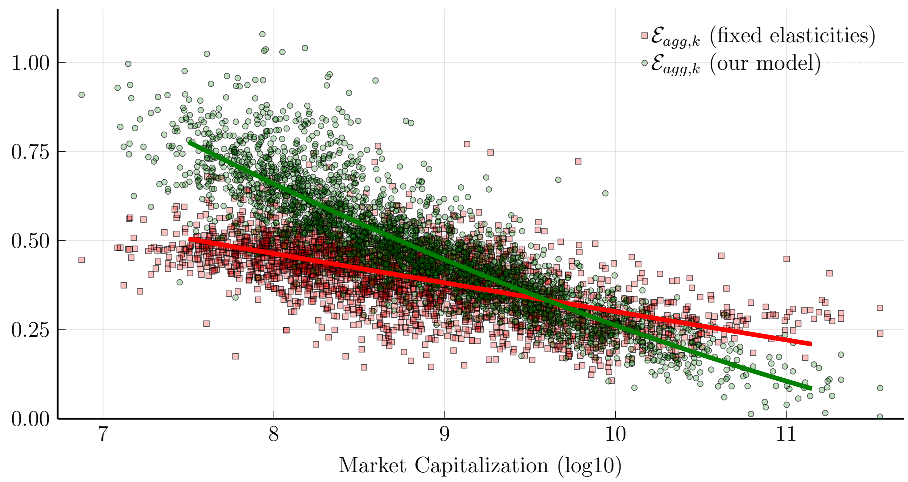

Figure 3. Aggregate elasticity at the stock level: $\mathcal{E}_{agg,k}$.
Figure 3 represents estimates of the aggregate elasticity $\mathcal{E}_{agg,k}$ as a function of their market capitalization (in logarithm) for the date 2011Q3. Each point represents a stock; green circles are our estimates, while red squares correspond to a model where elasticities are fixed.

its elasticity. Koijen and Yogo (2019) point out that large stocks tend to have more inelastic investors overall. Once we allow individual elasticities to respond to stock characteristics and the aggregate elasticity, the data reveals an additional source for this relation: the same investor behaves more inelastically for large stocks than small stocks. This additional source of variation within investor rather than across investors leads to a steeper relation between size and elasticity. For computational tractability, we estimate a linear relation between size and elasticity at the investor-level; this linearity yields the tiny values of elasticity for the very largest stocks.

Table 3 shows that these conclusions hold not only for this specific date, but across our sample. We report the distribution across dates of various statistics of the cross-section of $\mathcal{E}_{agg}$. In particular, we confirm that our estimates have a steeper relation between elasticity and stock size (Panel B), and less residual variation in elasticity across stocks (Panel C), by about 50%. These conclusions also remain unaltered under alternative specifications; Tables IA.2 and IA.3 show the same summary statistics for $\mathcal{E}_{agg}$ estimates from the specifications using 1-year lagged AUM for instrument construction and weighting investors by AUM (rows (2) and (10) in Table 2).

The negative relation between size and elasticity might appear surprising given existing evidence suggesting that large stocks are more informationally efficient.[46] However, there are good reasons

[46]See Lo and MacKinlay (1990), Jegadeesh and Titman (1993), Lakonishok et al. (1994), and Hong et al. (2000).

Table 3.
Properties of aggregate elasticity $\mathcal{E}_{agg}$

	Panel A: Statistics of average elasticity across stocks			
	Average	25th pct.	Median	75th pct.
Elasticity $\mathcal{E}_{agg}$	0.438	0.386	0.444	0.512
Fixed elasticity	0.39	0.358	0.389	0.443
	Panel B: Regression coefficient (by dates) of elasticity on size			
	Average	25th pct.	Median	75th pct.
Elasticity $\mathcal{E}_{agg}$	−0.0777	−0.0858	−0.0728	−0.067
Fixed elasticity	−0.0286	−0.0307	−0.0273	−0.0249
	Panel C: Residual cross-sectional standard deviation of elasticity			
	Average	25th pct.	Median	75th pct.
Elasticity $\mathcal{E}_{agg}$	0.0395	0.0339	0.0376	0.0438
Fixed elasticity	0.0842	0.0739	0.0828	0.0915

Table 3 presents statistics of the aggregate elasticity $\mathcal{E}_{agg,k,t}$. We estimate the elasticities in our baseline model and in a specification with fixed elasticities ($\chi = 0$ as in Koijen and Yogo (2019)). Panel A has summary statistics of the average elasticity by date. Panel B shows summary statistics of the coefficient β_t from the the regression $\mathcal{E}_{agg,k,t} = \alpha_t + \beta_t p_{k,t} + \varepsilon_{k,t}$ by date. Panel C reports summary statistics of the cross-sectional standard deviation of the residual from the regression described in Panel B. The sample period is 2001–2020.

to think that institutions are more reluctant to change their positions for large stocks than for small stocks. Mechanically, the largest stocks occupy a larger share of portfolios. As of July 2021, the five largest corporations in the U.S. stock market account for about 18% of total market capitalization.[47] As a consequence, a large change in portfolio weight would have a large effect on an institution's portfolio return. Many institutions are either benchmarked to the index or have hard dollar limits on how much they can trade a given stock, and hence they would be unwilling to take on such large changes. As an illustration, Figure 4 decomposes trading activity—the sum of squared relative change in portfolio position—across percentiles of portfolio weights; Appendix Section G details this calculation. There is much less trading activity for the larger portfolio positions: the top 50% of portfolio positions only account for 9% of trading activity. As such, the interpretation of our results is not so much that large stocks experience more mispricing but rather that high investor elasticity cannot be the explanation for the evidence on their returns.[48]

[47]The total market capitalization of Apple, Microsoft, Amazon, Alphabet (Google), and Facebook amount to $8.8tn for total U.S. market capitalization of $49tn.

[48]In the model of Section 3, both elasticity and the quantity of noise trading determine price informativeness.

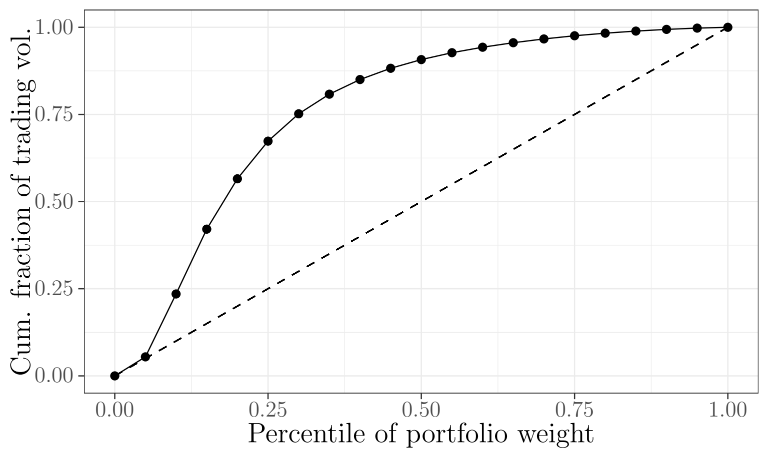

Figure 4. Trading activity across portfolio positions. Figure 4 presents the cumulative share of trading activity (defined in equation (IA.188)) by quantiles of investor portfolio weights. The dashed line is the 45 degree line.

6 Implications

6.1 The rise of passive investing

The last 20 years have seen a large increase in passive investing, a fact documented in French (2008). More recently, Stambaugh (2014) shows that both the fraction of mutual funds that are actively managed and the active share of the portfolio of active equity mutual funds have declined. The share of passive funds of the U.S. stock market has grown from nearly zero at the beginning of the 1990s to more than 15% in 2019. Concurrently, the share of active funds topped out at the end of the 1990s and has declined from 20% to 15% from 2000 to 2019 (see Figure IA.4).[49] Our model takes a more comprehensive view of who are the passive investors, not restricting ourselves to mutual funds.[50] With this approach we find on Figure 5 that the share of passive strategies has grown by 22 percentage points from 19% to 41% over the last 20 years. These larger numbers are consistent with the view that some institutions beyond mutual funds follow passive strategies,

Farboodi et al. (2021) use a richer structural model to decompose informativeness into data, growth, and volatility.

[49]We report the dollar numbers in Figure IA.5. Net assets of passive funds has grown from virtually zero to $5.4t in 2019, whereas the net assets of active funds only increased from $600b in 1993 to $5.5t in 2019.

[50]Our methodology for measuring passive investing as inelastic demand is described further in Appendix D.3. Each institution files a single 13F form, so this approach does not separate active and passive funds within the same institution.

or that some funds follow "closet indexing" strategies (Cremers and Petajisto, 2009). Chinco and Sammon (2022) find such a large passive investing share in line with our estimates in a completely different empirical strategy using excess volume around index reconstitutions.

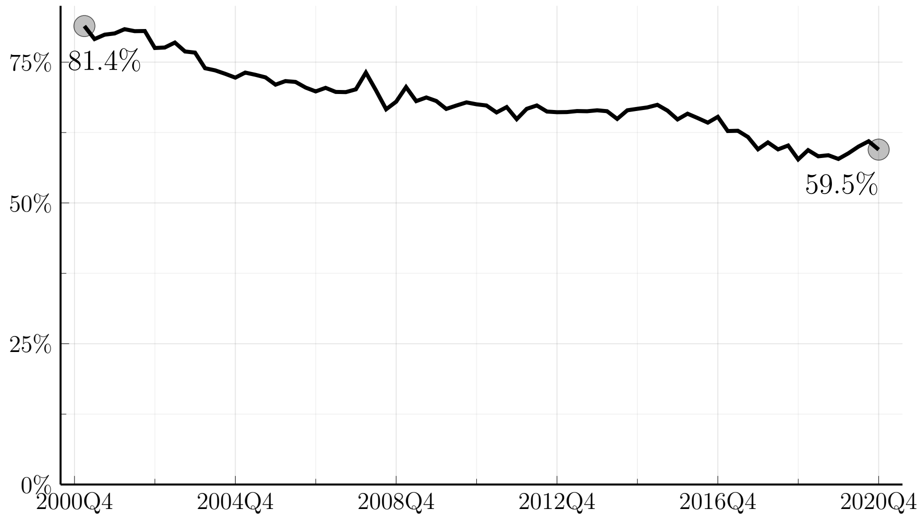

Figure 5. Fraction of active investors. Figure 5 reports the fraction of active investors according to our model. For each stock, we compute the ratio of total position of active investors and the market capitalization. We report the median across stocks.

Has the shift to passive portfolios impacted the behavior of prices? Understanding how investors react to changes in the behavior of other investors is crucial to answer this question. In the common view of "fiercely competitive markets," when some investors stop looking for profitable trading opportunities, some other investors step in to replace them; prices do not change. In contrast, if investors do not respond to others, the demand for stocks becomes more inelastic, which strongly affects the behavior of prices. For example in the theory of Section 3.1, more inelastic demand leads to prices that are more volatile and less informative. Our model, and in particular the parameter χ, accounts for the strength of this reaction. We use the estimated parameters to quantify the impact of the rise in passive investing on aggregate demand elasticities.

Starting with the demand system from Section 4, we consider the following counterfactual: we impose an exogenous change in the fraction of active investors and compute the new equilibrium elasticities. Of course the rise of passive investing is not a purely exogenous phenomemon. However, most plausible explanations of this phenomemon are independent from the rest of the demand system. For example, the development of financial technology made it cheaper to pursue passive strategies: fees on passive funds have dropped dramatically and ETFs have become available. Or, one subset of investors, maybe after listening to finance professors, realized they were making mistakes when pursuing active strategies.[51] Such shocks are equivalent to an exogenous change in the fraction of passive investors as long as they do not directly affect the demand of the remaining investors.

Computing the effect of the rise of passive investing corresponds to the calculation of equation (5), accounting for heterogeneous investors. Combining the individual demand elasticity $\mathcal{E}_{ik}$ in equation (14) with the equilibrium condition of (18), we have

$$\mathcal{E}_{agg,k} = |Active_k| \times \left(\sum_{i \in Active_k} \frac{w_{ik} A_i}{\sum_{j \in Active_k} w_{jk} A_j} \cdot \underline{\mathcal{E}}_{ik} - \chi \mathcal{E}_{agg,k} \right) \tag{26}$$

The aggregate elasticity combines three terms: (i) the fraction of the asset held by active investors, $|Active_k|$; (ii) the average baseline elasticity among active investors, weighted by their respective positions; and (iii) an adjustment for the strategic response of active investors to the aggregate elasticity, which depends on χ.[52]

From this expression we obtain the effect of a change in the fraction of active investing. Changing $|Active_k|$ while holding everything else constant corresponds to the assumption that the set of active investors that become passive is a representative sample of the active population. This leads to a simple formula:

$$\frac{d \log \mathcal{E}_{agg,k}}{d \log |Active_k|} = \frac{1}{1 + \chi \; |Active_k|}. \tag{27}$$

The pass-through from a rise in active investment to aggregate elasticity is determined by two numbers: the degree of strategic response χ and the fraction of active investors.[53] When χ is large,

[51] Bhamra and Uppal (2019) estimate sizable welfare costs from lack of diversification.

[52] Using equation (26), we can solve for the equilibrium value of aggregate elasticity

$$\mathcal{E}_{agg,k} = \sum_{i \in Active_k} \frac{w_{ik} A_i}{\sum_{j \in Active_k} w_{jk} A_j} \cdot \underline{\mathcal{E}}_{ik} \;\; \times |Active_k| \times \frac{1}{1 + \chi \; |Active_k|}.$$

[53] Appendix Section A.4 shows that with investor-specific χ_i, this expression remains unchanged, other than what matters now is the position-weighted average χ_i among active investors.

the aggregate elasticity does not respond to a shift in passive investing, and the pass-through is zero. At the opposite end, when $\chi = 0$ such that investors do not respond to market conditions, the pass-through is 100%; an increase in the fraction of passive investors translates into a one-to-one decrease in aggregate demand elasticity. Furthermore, because only active investors change their elasticities in response to others (passive investors always have an elasticity of zero), starting with a larger fraction of active investors leads to a smaller pass-through.

We can readily compute the pass-through: it solely depends on two observable quantities, χ and $|Active_k|$. In Section 4, we estimated the degree of strategic response and found that $\chi = 3$. Recall we measure the total quantity of passive investors as investors with an elasticity of zero in a Koijen-Yogo demand system. Not surprisingly, we find a trend down from 81% in 2001 to 59% in 2020. Taking the average across dates for the share of active investors, 68%, and for the degree of strategic response, $\chi = 3$, we find a value of the pass-through of[54]

$$\frac{1}{1 + \chi\ |Active_k|} = \frac{1}{1 + 3 \times 0.68} = 33\%. \tag{28}$$

This implies that the strategic response is strong enough to compensate about two thirds of the direct effect of a rise in passive investing. While substantial, this effect is far from the full cancellation of the idealized view of financial markets.

We multiply this pass-through by the rise in the proportion of passive investing to obtain the total effect on elasticity. We consider different takes for the size of the exogenous change. First we use our comprehensive measure of passive investing. The decline from 81% to 59% corresponds to a 32% drop, leading to elasticities lowered by $33\% \times 32\% = 11\%$. Translating the elasticities into price multipliers, this implies that the rise in passive investing causes an increase in the price impact of buying \$1 of a stock roughly from \$2.5 to \$2.8. Second, we look at a narrower measure of the rise in passive investing centered around the assets under management of passive mutual funds and ETFs. Their fraction of total market capitalization has increased by 15 percentage points in the last 30 years. Starting from a baseline of 81% of active investors, this change represents a

[54]When the share of active investors is at 81% as in 2001 the pass-through is 29%, while when this share is at its lowest value of 59% at the end of the sample it is 36.1%.

19% drop in the total fraction of active investors. With our pass-through of 0.33, this increase in passive investing by mutual funds reduces elasticities by 6.3%.

6.2 Decomposing the evolution of the demand for stocks

In the previous exercise, we isolated the causal effect of a change in passive investing on equilibrium demand elasticities. Next, we propose a positive account of the data: we decompose the actual changes in elasticity over the last twenty years in light of our model.

6.2.1 The evolution of aggregate elasticity

Figure 6 presents the time series of the distribution of equilibrium elasticities across stocks. For each date, we compute quantiles of the cross-section of aggregate elasticities, $\mathcal{E}_{agg,k}$. Elasticities increase until before the financial crisis, and have been decreasing since. The average elasticity (bold solid line) goes from 0.41 to 0.27. This pattern holds throughout the distribution of elasticities. Despite the growth of passive investing, the episode of declining elasticities in the second part of the sample might be surprising because of the intuition that markets are continuously becoming more liquid due to the evolution of trading technologies. However, such a trend is not specific to our model estimates: Koijen and Yogo (2019) find similar behavior towards the end of their sample, and Koijen et al. (2020) attribute a large part of the decline in active trading to a decrease in elasticity between 2007 and 2019. Consistent with slower improvements in trading, microstructure measures of liquidity also do not particularly improve over the latter part of the sample. For example, Chordia et al. (2011) document sharp improvements in Lee-Ready effective spreads until the early 2000s which then plateau (see also Frazzini et al. (2018), Rösch et al. (2016)). In the next section, we further our understanding of what is behind the evolution of demand elasticities through a simple decomposition.

6.2.2 Sources of change in elasticity

In Section 4, we estimated the demand elasticities for each investor-stock in each quarter from 2001 to 2020. While our identification strategy focuses on the cross-section, we can use the time-series

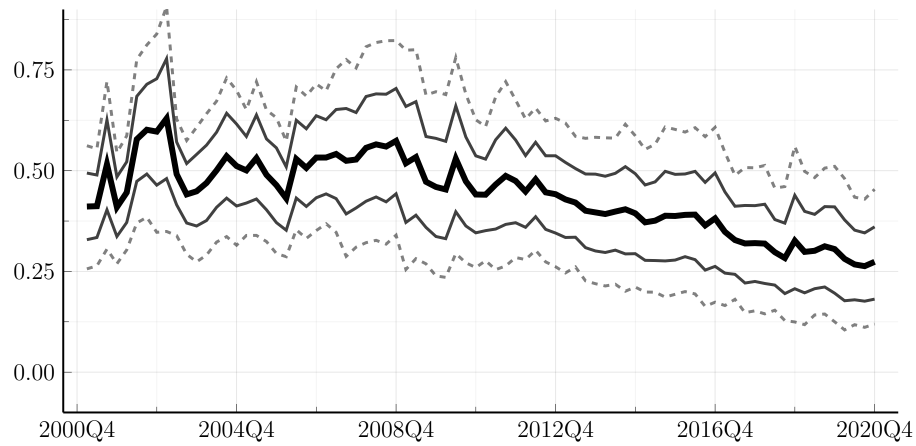

Figure 6. Distribution of aggregate elasticity across stocks. Figure 6 traces out the distribution of aggregate elasticity $\mathcal{E}_{agg,k}$ over time. The bold line represents the average elasticity across stocks for each year. The solid lines represents the 25th and 75th percentile and the dashed lines the 10th and 90th percentile.

dimension of our estimates as a description of the evolution of the demand for stocks over time.

We decompose changes in elasticity from year to year into three components by differentiating equation (26). We denote by $\langle \underline{\mathcal{E}}_{ik} \rangle$ the position-weighted average of the individual-specific component of the elasticity of active investors, $\underline{\mathcal{E}}_{ik}$; this corresponds to the second term in equation (26). We derive the effect of a change in investor composition,

$$\underbrace{\frac{d\mathcal{E}_{agg,k}}{\mathcal{E}_{agg,k}}}_{\text{Change in aggregate elasticity}} = \underbrace{\frac{d|Active_k|}{|Active_k|}}_{\text{Share of active investors}} + \underbrace{|Active_k| \cdot \frac{d\langle \underline{\mathcal{E}}_{ik} \rangle}{\mathcal{E}_{agg}}}_{\text{Individual elasticity of active investors}} - \underbrace{\chi |Active_k| \frac{d\mathcal{E}_{agg}}{\mathcal{E}_{agg}}}_{\text{Strategic response}} . \tag{29}$$

The first component accounts for changes in the share of active investors over time and their ultimate effect on the elasticities. The second component corresponds to changes in the average individual-level elasticity component of active investors; how their own characteristics contribute to the elasticity. These forces correspond respectively to the extensive and intensive margin of individual elasticities. The last component corresponds to the strategic response to these two changes. If $\chi = 0$ there is no strategic response and this term disappears. Otherwise, the strategic response compensates the direct effects of both the share of active investors and their composition.

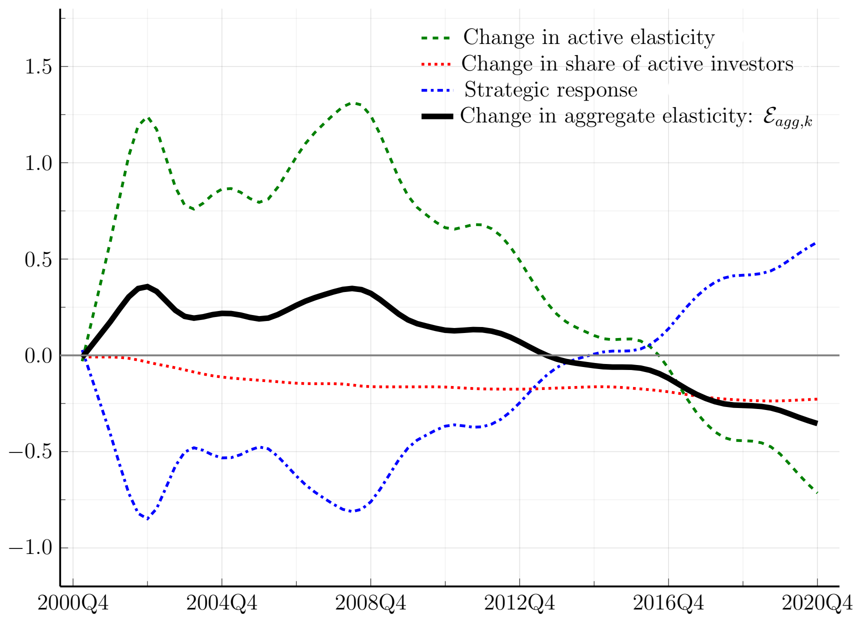

Figure 7. Decomposition of the change in aggregate elasticity. Figure 7 shows the decomposition derived in equation (29) over time. We compute each term of the decomposition for each date and accumulate the changes over time, scaled by the initial aggregate elasticity.

We accumulate the three terms of this decomposition over time in Figure 7 (Figures IA.7 and IA.8 find similar results for alternative model specifications).[55] We smooth the series to make the secular trends easier to identify. Consistent with the importance of the rise in passive investing discussed in Section 6.1, we find that the direct effect of the decrease in the fraction of active investors has a similar magnitude to the total change in aggregate elasticities. Interestingly, investors also change their own elasticities at the intensive margin. While individual elasticities increase until the financial crisis, they experience a sharp drop afterward, driving the hump-shaped evolution of aggregate elasticities in Figure 6. Appendix Figure IA.6 confirms this pattern holds in the entire cross-section of investors. Consistent with this move towards more passive strategies at the intensive margin, Pavlova and Sikorskaya (2023) document a trend down in the tracking error of active mutual funds. In net, this second direct force also contributes to a drop in aggregate elasticities. However, the strategic response strongly mitigates these individual changes in equilibrium. The strategic response reverses around two thirds of the decline.

[55] Because we cannot continuously integrate equation (29), we use the natural discrete approximation of the first and third terms and compute the second one as a residual.

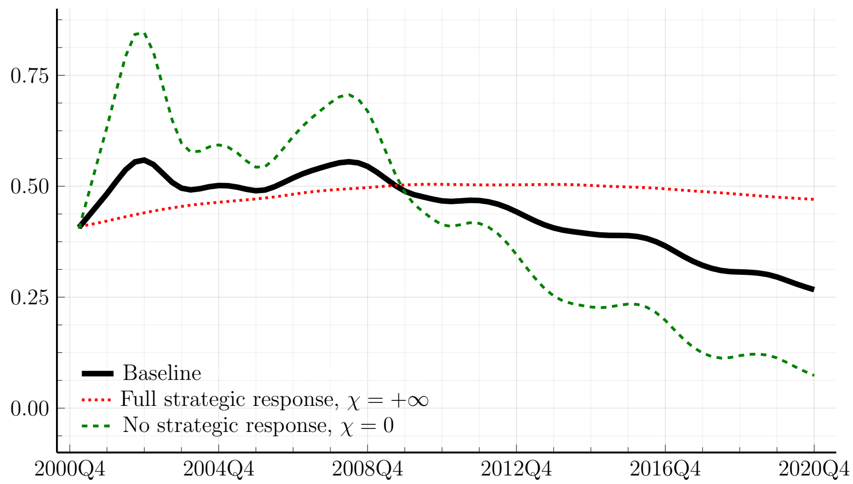

Figure 8. The evolution of aggregate elasticity under alternative competition regimes. Figure 8 shows the evolution of aggregate elasticity $\mathcal{E}_{agg,k}$ under alternative strategic regimes. The bold black line presents our baseline estimate. The dotted red line shows the elasticity with strong strategic response ($\chi \to \infty$). The dashed green line shows the elasticity with no strategic response ($\chi = 0$).

6.2.3 Evolution under counterfactual degrees of strategic response

Finally, we ask how the changes in the individual components of investor demand would have affected the aggregate elasticities under different strategic regimes. We start from the equilibrium levels of demand elasticity at the beginning of our sample (2001Q1). We feed into the model the two direct components highlighted above: how individual elasticities, $\underline{\mathcal{E}}_{ik}$, change over time and who becomes passive. We make different assumptions on how investors react to changes in the behavior of others. We show the time series of the results in Figure 8. The solid black line represents the actual evolution of the average aggregate elasticity across stocks; the colored dashed and dotted lines show the counterfactual results.

We first consider the case where interactions are strongest, corresponding to $\chi \to +\infty$. In this situation, any change in individual behavior is completely counteracted by other investors. The aggregate elasticities for each stock are pinned down at their initial level. The only source of variation in the average elasticity over time are changes in the composition of the universe of stocks. This is the dotted red line in Figure 8, which experiences very little change over our sample. This result also confirms that the patterns in aggregate elasticities we have documented is not the consequence of changes in which stocks are traded.

The other extreme is the situation where investors do not react to others at all and $\chi = 0$. Then, all the changes in individual investor behavior directly feed into aggregate elasticities. This leads to a more dramatic drop in elasticities over time than our baseline estimates. This is the dashed green line in Figure 8. We observe a strong decrease, about twice as large as the baseline.

Overall these results confirm that changes in the behavior of investors have profoundly changed the aggregate demand curves for individual stocks. Competition among investors in setting their strategies played an important role in mitigating the total impact of those changes. However, the strategic response was not strong enough to fully negate the course of a downward trend in aggregate elasticities.

6.3 Implications in the cross-section of stocks

6.3.1 The strategic response in the cross-section

In our model, the response to a change in the share of passive investors occurs through the strategic response: the other active investors change their elasticity. However, other types of adjustments could happen. For example, the composition of active investors could change. Also, the identity of who becomes passive might shape the response beyond their demand elasticity, as is the case in some more sophisticated theories.

While these possibilities are not explicitly part of our empirical model, they would manifest themselves through the changes in aggregate elasticity in response to changes in passive investing. We investigate their presence by zooming in on sources of variation in passive investing different from the ones driving our baseline estimates. We regress annual log changes in stock-level elasticity on changes in the fraction of active investors:

$$\log(\mathcal{E}_{agg,k,t}) - \log(\mathcal{E}_{agg,k,t-1}) = \beta \left(\log(|Active_{k,t}|) - \log(|Active_{k,t-1}|)\right) + \alpha_k + \gamma_t + e_{k,t}. \qquad (30)$$

The inclusion of time and stock fixed effects allows to focus on variation independent of the average variation. A benchmark value for the coefficient β is the pass-through from equation (27), about one third. However, if changes in individual-level elasticities, or other types of changes in investor composition, are correlated with the active share, this would push β away from the theoretical pass-through. So effectively, we are assessing whether changes in investor behavior beyond the strategic response are correlated with changes in passive investing.

Table 4 presents the results. Column 1 is a univariate regression; columns 2 and 3 add date then stock fixed effects. We find coefficients close to the theoretical pass-through of a third in all specifications but the raw OLS case, with a value of 0.26.[56] This result supports the interpretation that our measured degree of strategic response is the main driver of the response of aggregate elasticity to changes in passive investing.

We also consider what happens around index inclusions and exclusions. For these events, the source of the variation in passive investing is known because index funds are forced to change their portfolio after reclassification. Following Chang et al. (2014), Ben-David et al. (2018), and Chinco and Sammon (2022), we exploit the mechanical rule that allocates stocks between the Russell 1000 and 2000 indexes.[57] We use the index-switching event as an instrument for the share of passive investors; column 5 of Table 4 reports the result. The first stage is significant with reclassification changing active ownership by about 5% (see Appendix Table IA.5).[58] The coefficient is 0.35, again very close to the theoretical pass-through.

Figure IA.3 further confirms the robustness of the pass-through. We estimate the model over samples of 1 year or 1 quarter. While the estimated pass-through exhibits noise due to the shorter samples, no particular time trend emerges, suggesting stability over time in strategic responses. This result is further substantiated by Table IA.4 that shows that the pass-through based on quarterly estimates for χ is still robust to focusing on different sources of variation in passive investing.

6.3.2 Behavior of asset prices

Our empirical model focuses on the estimation of demand elasticities for two reasons. First, elasticities are the quantity through which investor strategic interactions manifest themselves across

[56]Statistical significance is not completely meaningful in this setting, because the left-hand-side of the regression is model-generated.

[57]We are grateful to Alex Chinco for sharing his data with us.

[58]Glossner (Forthcoming) documents no change in institutional ownership around reclassifications. This suggests our variation is coming from a change in the composition of institutions.

Table 4. Changes in aggregate stock-level elasticity $\mathcal{E}_{agg,k}$ on the active share

	Log Change in Elasticity				
	(1)	(2)	(3)	(4)	(5)
Change in Active share	0.259***	0.385***	0.368***	0.346***	0.346***
	(0.059)	(0.022)	(0.022)	(0.021)	(0.054)
Date Fixed Effects		Yes	Yes	Yes	Yes
Stock Fixed Effects			Yes		
Controls				Yes	Yes
Estimator	OLS	OLS	OLS	OLS	IV
N	50,292	50,292	49,661	50,292	10,619
R^2	0.028	0.612	0.637	0.695	0.696
First-stage F statistic					9.444
First-stage p value					0.000

Table 4 reports a panel regression of annual log change in stock level elasticity $\mathcal{E}_{agg,k}$ on the annual log change in the active share $|Active_k|$. Column 2 adds date fixed effects. Column 3 adds stock fixed effects. Column 4 uses date fixed effects and controls for lagged book equity and annual log changes of log book equity. Column 5 instruments the log change in the active share $|Active_k|$ between Q1 and Q2 in any given year by two indicator variables corresponding to stocks switching between Russell 1000 and 2000 in either direction. In this column, the sample is restricted to stocks with CRSP market capitalization ranked between 500 to 1500 as of the end of Q1. The sample period is 2001–2020 for columns 1-4, and 2007–2020 for column 5. Standard errors are 2-way clustered by date and stock.

many theories. Second, these elasticities are a key determinant of the behavior of asset prices. For example, all else equal, aggressive investors limit the influence of excess fluctuations in prices, which often results in less volatility or more price informativeness.[59] Similarly, an asset with highly elastic investors will tend to be more liquid, because these investors are willing to provide liquidity. In this section, we document the relation between aggregate elasticity and some of these aspects of asset prices in the cross-section.

In the spirit of our structural model, we run the following regressions:

$$Y_{k,t} = \beta \mathcal{E}_{agg,k,t} + \gamma_t' X_{k,t} + \alpha_t + e_{k,t}, \tag{31}$$

where $Y_{k,t}$ is a stock-level outcome, $X_{k,t}$ controls for stock characteristics, and α_t are time fixed effects. This OLS specification is likely biased because $\mathcal{E}_{agg,k,t}$ correlates with unobserved aspects

[59]In the theories we considered, this corresponds to holding the quantity of noise trading constant.

of the stocks, in particular the demand shocks $\epsilon_{i,k,t}$. Therefore, our preferred specification is 2SLS in which we instrument for $\mathcal{E}_{agg,k,t}$ using $\hat{\mathcal{E}}_{agg,k,t}$. Appendix Table IA.6 confirms that the first stage is strongly significant, like for the model of Section 4.3.2.

Table 5 reports the results. In columns 1 to 4, we measure the effect of aggregate elasticity on daily stock volatility. The first two columns use total volatility and the latter two use idiosyncratic volatility (from the three-factor model of Fama and French (1993)). While the relation is weak without instrumenting, the IV specifications reveal a strongly negative relation. Consistent with most theories, stocks with more elastic investors have less volatile returns. This result also ties together our mechanism with the results of Ben-David et al. (2018) on index inclusions. When a stock has more passive investors following an index switch, its aggregate elasticity declines due to a low value of χ (Table 4), which results in more volatility, as documented in their paper.

Columns 5 and 6 consider the measure of price informativeness of Dávila and Parlatore (2018). The point estimates suggest that assets with more elastic demand have more informative prices, but the estimates are not statistically significant. The large standard errors reveal that the relation is difficult to estimate precisely rather than a tight zero. A number of papers attempt to measure directly the effect of passive investing on price informativeness, with conflicting findings. Sammon (2021) shows that an increase in passive ownership leads to a decrease in price informativeness while Coles et al. (2022) estimate that there is no effect. Columns 7 and 8 use the illiquidity measure of Amihud (2002). The IV specification is consistent with the theory: illiquidity is lower for stocks with more elastic investors. An interesting aspect of this connection is that our elasticity estimates focus on low-frequency aspects of portfolios while the Amihud (2002) measure highlights high-frequency properties of returns.

Similarly to the case of volatility, the OLS estimate is larger than the IV estimate. To understand the source of this pattern, note that demand shocks ϵ_{ikt} increasing demand from active investors relative to passive investors lead to higher aggregate elasticity than accounted by the instrument. The difference between specifications suggests that such demand shocks directly lead to higher return volatility — e.g. if their level is correlated with their volatility — and illiquidity, and that this direct link dominates their impact through changes in aggregate demand elasticity.

Overall, these results support the view that estimating the demand for stocks is useful to get to a better understanding of the behavior of financial markets. Specifically, demand elasticities appear to shape many aspects of this behavior.

7 Conclusion

The idea that investors interact with each other is fundamental in financial markets. A classic hypothesis, motivated by the view of "fiercely competitive markets," states that changes in a group of investors' behavior have no impact on prices because others step in to compensate. Many theories of financial decisions work through strategic responses: how others trade affects how you trade. While strategic responses permeate all of finance, an empirical understanding of their importance remains elusive. We put forward a framework that enables measurement of the degree of strategic response and the analysis of its impact on equilibrium outcomes.

In the US stock market we find evidence that investors do react to each other: when an investor is surrounded by less aggressive traders, she trades more aggressively. However, this response is much weaker than anticipated by the classic hypothesis. Strategic responses compensate only two thirds of the effect of changes in investor behavior on the aggregate demand for a stock. This implies that the rise in passive investing leads to substantially more inelastic markets.

The ability to measure strategic responses opens a new path to address many other important issues in finance. To assess the impact of financial regulation on some market participants, for example the Basel III leverage constraint on banks, one cannot ignore how other institutions will respond. Likewise, to understand how the distress of some financial institutions creates fire-sale spillovers, one must realize that other investors will step up. Our framework measures how many actually will. Recent work in international finance emphasizes the importance of cross-border flows and global imbalances. What happens if a large sovereign institution stops investing in one market, like China with US treasuries? Again, strategic interactions among investors will be a crucial input in determining the final impact of such a momentous shift. Moreover, the rise and availability of big data promises to change the landscape of how financial institutions compete with each other.

Table 5. Stock-level elasticities $\mathcal{E}_{agg,k}$ and the behavior of asset prices

	Total Volatility		Idiosyncratic Volatility		Price informativeness		Illiquidity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Elasticity	-0.059	-0.383^{***}	-0.040	-0.261^{***}	0.019	0.259	0.750^{***}	-0.397^{***}
	(0.049)	(0.123)	(0.041)	(0.099)	(0.186)	(0.474)	(0.067)	(0.131)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	IV	OLS	IV	OLS	IV	OLS	IV
N	222,359	222,359	208,969	208,969	67,376	67,376	219,780	219,780
R^2	0.218	0.208	0.247	0.241	0.020	0.018	0.714	0.619

Table 5 reports panel regressions of measures of volatility, price informativeness and illiquidity on stock level elasticity $\mathcal{E}_{agg,k}$. All variables are demeaned and standardized for each date. Odd columns show results from OLS regressions. Even columns show results from instrumental variables regressions that use our instrument for stock elasticity defined in equation (24). For columns (1) and (2), we compute the total daily volatility of stocks. For columns (3) and (4) we compute daily idiosyncratic volatility with respect to the Fama and French (1993) three-factor model based on daily CRSP data within a quarter. Columns (5) and (6) take the measure of price informativeness provided by Dávila and Parlatore (2018). Columns (7) and (8) use the Amihud (2002) measure for illiquidity as the dependent variable, calculated again based on daily CRSP data within a quarter. All specifications are weighted by lagged market equity. We follow our main specification for the estimation of elasticity and control non-linearly for book equity. The sample period starts in 2001 for all columns, and ends in 2020 for specifications 3–4 and 7–8, 2019 for specifications 1–2, and 2017 for specifications 5–6, based on respective data availability. Standard errors are 2-way clustered by date and stock.

References

Amihud, Yakov, "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets*, 2002, *5* (1), 31–56.

Angeletos, George-Marios and Chen Lian, "Forward Guidance without Common Knowledge," *American Economic Review*, September 2018, *108* (9), 2477–2512.

Azarmsa, Ehsan and Carter Davis, "Is Asset Demand Elasticity Set at the Household or Intermediary Level?," *Available at SSRN*, 2023.

Backus, Matthew, Christopher Conlon, and Michael Sinkinson, "Common ownership in America: 1980-2017," Technical Report, National Bureau of Economic Research 2019.

_ , Christopher T Conlon, and Michael Sinkinson, "Common Ownership Data: Scraped SEC form 13F filings for 1999-2017," 2020.

Bai, Jennie, Thomas Philippon, and Alexi Savov, "Have financial markets become more informative?," *Journal of Financial Economics*, 2016, *122* (3), 625–654.

Balasubramaniam, Vimal, John Y Campbell, Tarun Ramadorai, and Benjamin Ranish, "Who Owns What? A Factor Model for Direct Stockholding," Mimeo, Harvard University 2021.

Bastianello, Francesca and Paul Fontanier, "Partial Equilibrium Thinking in General Equilibrium," Technical Report, Harvard 2021.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, "Do ETFs Increase Volatility?," *The Journal of Finance*, 2018, *73* (6), 2471–2535.

Bhamra, Harjoat S. and Raman Uppal, "Does Household Finance Matter? Small Financial Errors with Large Social Costs," *American Economic Review*, March 2019, *109* (3), 1116–54.

Bond, Philip and Diego García, "The equilibrium consequences of indexing," Mimeo, University of Washington 2018.

Brunnermeier, Markus K and Yuliy Sannikov, "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 2013, *Forthcomin.*

Bulow, Jeremy I., John D. Geanakoplos, and Paul D. Klemperer, "Multimarket Oligopoly: Strategic Substitutes and Complements," *Journal of Political Economy*, 1985, *93* (3), 488–511.

Buss, Adrian and Savitar Sundaresan, "More risk, more information: How passive ownership can improve informational efficiency," Mimeo 2020.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, "Regression Discontinuity and the Price Effects of Stock Market Indexing," *The Review of Financial Studies*, 07 2014, *28* (1), 212–246.

Chevalier, Judith and Glenn Ellison, "Risk Taking by Mutual Funds as a Response to Incentives," *Journal of Political Economy*, 1997, *105* (6), 1167–1200.

Chinco, Alex and Marco Sammon, "Excess Reconstitution-Day Volume," Mimeo, CUNY, Baruch College 2022.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, "Recent trends in trading activity and market quality," *Journal of Financial Economics*, 2011, *101* (2), 243–263.

Cochrane, John H., "Eugene Fama: Efficient markets, risk premiums, and the Nobel Prize," 2013. Mimeo: University of Chicago.

Coles, Jeffrey L., Davidson Heath, and Matthew C. Ringgenberg, "On Index Investing," *Journal of Financial Economics*, 2022, *145* (3), 665–683.

Cremers, K. J. Martijn and Antti Petajisto, "How Active Is Your Fund Manager? A New Measure That Predicts Performance," *The Review of Financial Studies*, 08 2009, *22* (9), 3329–3365.

Dávila, Eduardo and Cecilia Parlatore, "Identifying price informativeness," Mimeo, National Bureau of Economic Research 2018.

Dou, Winston, Leonid Kogan, and Wei Wu, "Common fund flows: Flow hedging and factor pricing," *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*, 2020.

Eisfeldt, Andrea L, Hanno Lustig, and Lei Zhang, "Complex asset markets," Technical Report, National Bureau of Economic Research 2017.

Eyster, Erik and Matthew Rabin, "Cursed Equilibrium," *Econometrica*, 2005, *73* (5), 1623–1672.
_ , _ , **and Dimitri Vayanos**, "Financial Markets Where Traders Neglect the Informational Content of Prices," *The Journal of Finance*, 2019, *74* (1), 371–399.
Fama, E F and K R French, "The cross-section of expected stock returns," *Journal of finance*, 1992, *47* (2), 427–465.
Fama, Eugene F. and Kenneth R. French, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 1993, *33* (1), 3–56.
Farboodi, Maryam, Adrien Matray, Laura Veldkamp, and Venky Venkateswaran, "Where has all the data gone?," Technical Report, RFS Forthcoming 2021.
_ **and Laura Veldkamp**, "Long-Run Growth of Financial Data Technology," *American Economic Review*, August 2020, *110* (8), 2485–2523.
Farhi, Emmanuel and Iván Werning, "Monetary Policy, Bounded Rationality, and Incomplete Markets," *American Economic Review*, November 2019, *109* (11), 3887–3928.
Frazzini, Andrea, Ronen Israel, and Tobias J Moskowitz, "Trading costs," *Available at SSRN 3229719*, 2018.
French, Kenneth R., "Presidential Address: The Cost of Active Investing," *The Journal of Finance*, 2008, *63* (4), 1537–1573.
Gabaix, Xavier, "A Behavioral New Keynesian Model," *American Economic Review*, August 2020, *110* (8), 2271–2327.
_ **and Matteo Maggiori**, " International Liquidity and Exchange Rate Dynamics," *The Quarterly Journal of Economics*, 03 2015, *130* (3), 1369–1420.
_ **and Ralph SJ Koijen**, "In search of the origins of financial fluctuations: The inelastic markets hypothesis," Mimeo, Harvard University 2020.
_ **, Arvind Krishnamurthy, and Olivier Vigneron**, "Limits of Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market," *The Journal of Finance*, 2007, *62* (2), 557–595.
Gârleanu, Nicolae and Lasse Heje Pedersen, "Efficiently Inefficient Markets for Assets and Asset Management," *The Journal of Finance*, 2018, *73* (4), 1663–1712.
_ **and** _ , "Active and Passive Investing: Understanding Samuelson's Dictum," *The Review of Asset Pricing Studies*, 08 2021. raab020.
_ , _ , **and Allen M. Poteshman**, "Demand-Based Option Pricing," *The Review of Financial Studies*, 02 2009, *22* (10), 4259–4299.
Glossner, Simon, "Russell Index Reconstitutions, Institutional Investors, and Corporate Social Responsibility," *Critical Finance Review*, Forthcoming.
Gourinchas, Pierre-Olivier, Walker Ray, and Dimitri Vayanos, "A preferred-habitat model of term premia and currency risk," Mimeo, Berkeley 2019.
Greenwood, Robin and Dimitri Vayanos, "Bond Supply and Excess Bond Returns," *The Review of Financial Studies*, 01 2014, *27* (3), 663–713.
_ **and Samuel G. Hanson**, "Waves in Ship Prices and Investment," *The Quarterly Journal of Economics*, 11 2014, *130* (1), 55–109.
_ **, Samuel G Hanson, Jeremy C Stein, and Adi Sunderam**, "A Quantity-Driven Theory of Term Premiums and Exchange Rates," Mimeo, Harvard University 2019.
Grossman, Sanford J and Joseph E Stiglitz, "On the Impossibility of Informationally Efficient Markets," *American Economic Review*, June 1980, *70* (3), 393–408.
Haddad, Valentin, Alan Moreira, and Tyler Muir, "When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed's Response," *The Review of Financial Studies*, 01 2021. hhaa145.
_ **and David Sraer**, "The Banking View of Bond Risk Premia," *The Journal of Finance*, 2020, *75* (5), 2465–2502.
_ **and Tyler Muir**, "Do Intermediaries Matter for Aggregate Asset Prices?," *Journal of Finance*, 2021, *76* (6), 2719–2761.

He, Zhiguo and Arvind Krishnamurthy, "Intermediary Asset Pricing," *American Economic Review*, 2013, *103* (2), 732–770.

Hirshleifer, David, "Presidential Address: Social Transmission Bias in Economics and Finance," *Journal of Finance*, 2020, *75* (4), 1779–1831.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, "Social Interaction and Stock-Market Participation," *The Journal of Finance*, 2004, *59* (1), 137–163.

_ , Terence Lim, and Jeremy C. Stein, "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies," *The Journal of Finance*, 2000, *55* (1), 265–295.

Huebner, Paul, "The Making of Momentum: A Demand-System Perspective," *Available at SSRN 4395945*, 2023.

Investment Company Institute, *Investment Company Fact Book — A Review of Trends and Activities in the Investment Company Industry*, 60 ed., ICI, 2020.

Jegadeesh, Narasimhan and Sheridan Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 1993, *48* (1), 65–91.

Jiang, Zhengyang, Robert Richmond, and Tony Zhang, "A portfolio approach to global imbalances," Mimeo 2020.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, "A Rational Theory of Mutual Funds' Attention Allocation," *Econometrica*, 2016, *84* (2), 571–626.

Kacperczyk, Marcin T, Jaromir B Nosal, and Savitar Sundaresan, "Market power and price informativeness," Mimeo, Imperial College 2020.

Kleibergen, Frank and Richard Paap, "Generalized reduced rank tests using the singular value decomposition," *Journal of Econometrics*, 2006, *133* (1), 97–126.

Koijen, Ralph S. J. and Motohiro Yogo, "A Demand System Approach to Asset Pricing," *Journal of Political Economy*, 2019, *127* (4), 1475–1515.

Koijen, Ralph SJ and Motohiro Yogo, "Exchange rates and asset prices in a global demand system," Mimeo, National Bureau of Economic Research 2020.

Koijen, Ralph S.J., François Koulischer, Benoît Nguyen, and Motohiro Yogo, "Inspecting the mechanism of quantitative easing in the euro area," *Journal of Financial Economics*, 2021, *140* (1), 1–20.

Koijen, Ralph SJ, Robert J Richmond, and Motohiro Yogo, "Which Investors Matter for Equity Valuations and Expected Returns?," Mimeo, National Bureau of Economic Research 2020.

Kreps, David M. and Jose A. Scheinkman, "Quantity Precommitment and Bertrand Competition Yield Cournot Outcomes," *The Bell Journal of Economics*, 1983, *14* (2), 326–337.

Kyle, Albert S., "Informed Speculation with Imperfect Competition," *The Review of Economic Studies*, 07 1989, *56* (3), 317–355.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, "Contrarian Investment, Extrapolation, and Risk," *The Journal of Finance*, 1994, *49* (5), 1541–1578.

Lee, Jeongmin, "Passive Investing and Price Efficiency," Mimeo 2020.

Lo, Andrew W. and A. Craig MacKinlay, "When Are Contrarian Profits Due to Stock Market Overreaction?," *The Review of Financial Studies*, 04 1990, *3* (2), 175–205.

Long, J. Bradford De, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, "Noise Trader Risk in Financial Markets," *Journal of Political Economy*, 1990, *98* (4), 703–738.

Lucas, Robert E, "Asset Prices in an Exchange Economy," *Econometrica*, 1978, *46* (6), pp. 1429–1445.

Malikov, George, "Information, participation, and passive investing," Mimeo 2019. Working Paper.

Manski, Charles F., "Identification of Endogenous Social Effects: The Reflection Problem," *The Review of Economic Studies*, 1993, *60* (3), 531–542.

Pavlova, Anna and Taisiya Sikorskaya, "Benchmarking intensity," *The Review of Financial Studies*, 2023, *36* (3), 859–903.

Petajisto, Antti, "Why Do Demand Curves for Stocks Slope Down?," *Journal of Financial and Quantitative Analysis*, 2009, *44* (5), 1013–1044.

Rösch, Dominik M., Avanidhar Subrahmanyam, and Mathijs A. van Dijk, "The Dynamics of Market Efficiency," *The Review of Financial Studies*, 10 2016, *30* (4), 1151–1187.

Rostek, Marzena and Marek Weretka, "Price inference in small markets," *Econometrica*, 2012, *80* (2), 687–711.

Rostek, Marzena J and Ji Hee Yoon, "Imperfect Competition in Financial Markets: Recent developments," *Working Paper*, 2023.

Sammon, Marco, "Passive Ownership and Price Informativeness," Mimeo 2021.

Shleifer, Andrei, "Do Demand Curves for Stocks Slope Down?," *The Journal of Finance*, 1986, *41* (3), 579–590.

_ **and Robert W. Vishny**, "The Limits of Arbitrage," *The Journal of Finance*, 1997, *52* (1), 35–55.

Siriwardane, Emil, Aditya Sunderam, and Jonathan Wallen, "Segmented Arbitrage," Technical Report, Working paper, HBS 2021.

Siriwardane, Emil N., "Limited Investment Capital and Credit Spreads," *The Journal of Finance*, 2019, *74* (5), 2303–2347.

Sirri, Erik R. and Peter Tufano, "Costly Search and Mutual Fund Flows," *The Journal of Finance*, 1998, *53* (5), 1589–1622.

Stambaugh, Robert F., "Presidential Address: Investment Noise and Trends," *The Journal of Finance*, 2014, *69* (4), 1415–1453.

Subrahmanyam, Avanidhar, "A Theory of Trading in Stock Index Futures," *The Review of Financial Studies*, 05 1991, *4* (1), 17–51.

Thaler, Richard, *Misbehaving: The Making of Behavioral Economics*, W. W. Norton & Company, 2015.

van der Beck, Philippe, "On the estimation of demand-based asset pricing models," Technical Report, Swiss Finance Institute 2022.

Vayanos, Dimitri and Jean-Luc Vila, "A Preferred-Habitat Model of the Term Structure of Interest Rates," *Econometrica*, 2021, *89* (1), 77–112.

_ **and Tan Wang**, "Search and endogenous concentration of liquidity in asset markets," *Journal of Economic Theory*, 2007, *136* (1), 66 – 104.

Veldkamp, Laura L., *Information Choice in Macroeconomics and Finance*, Princeton University Press, 2011.

Vives, Xavier, "Strategic supply function competition with private information," *Econometrica*, 2011, *79* (6), 1919–1966.

Warther, Vincent A., "Aggregate mutual fund flows and security returns," *Journal of Financial Economics*, 1995, *39* (2), 209–235.