How Competitive is the Stock Market? Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing*

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Abstract

We develop a framework to theoretically and empirically analyze how investors compete with each other in financial markets. In the classic view that markets are fiercely competitive, if a group of investors changes its behavior, other investors adjust their strategies such that nothing happens to prices. We propose a demand system with a flexible degree of strategic response and estimate it for institutional investors in the U.S. stock market. Investors react to the behavior of others in the market: when less aggressive traders surround an investor, she trades more aggressively. However, this strategic reaction is not nearly as strong as the classic view. Our estimates suggest that when a group of investors changes its behavior, the response of other investors only counteracts half of the direct impact. This result implies that the rise in passive investing over the last 20 years has led to substantially more inelastic aggregate demand curves for individual stocks by about 15%.
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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. In the standard view that "financial markets are fiercely competitive," 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 U.S. 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 standard view of "competitive financial markets." Our estimates suggest that this strategic response reduces the impact of an increase in passive investing by half. 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 15%.

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.

[1] For example, the ICI factbook (ICI, 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 "individual handwave argument."

Second, we provide a framework to quantify this competition in strategies and its 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 equilibrium result of investors' interactions. Third, we estimate the model using detailed portfolio positions of institutional investors in the U.S. 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 her 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 the idealized view where markets are fiercely competitive and there is always somebody on the lookout for good deals, 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 the 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, Rabin, and Vayanos, 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]

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.

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

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 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 competition map to the structure of our model.

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, and the equilibrium market elasticity remains unchanged. This situation corresponds to the ideal 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 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 2.2. We confirm the robustness of this finding in a battery of specifications: alternative instrument construction, more weights on large investors, additional controls, etc. Across these specifications, the estimated strategic response remains between 1.9 and 2.5. 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 competitive 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 0.4. A little less than half of a change in the fraction of active investors translates into a reduction in demand elasticity. Given the 30% decrease in active investing over the last 20 years, this effect yields a reduction in elasticities of 13%. 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. Again, this prediction highlights that while the effects of competition in strategies are strong, the stock market is far from the standard view. When "financial markets are competitive", the pass-through is 0, in which case a rise in passive investing has no impact. On the other hand, without strategic effects, the pass-through is 1, leading to a 30% decrease in elasticity.

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, competition 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 0.4 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. The entire cross-sectional distribution of stock-level elasticity decreased during that period by 40%. Interestingly, the model attributes this drop equally to two investor-specific sources of change. 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.[4] 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. However, another aspect played an important role: active investors also increased their equilibrium elasticity in response to the broad decrease in aggregate elasticities. In a counterfactual exercise in which we shut down the strategic responses, we find that elasticities would have decreased twice as much. In contrast, they would have barely moved with strong strategic responses.

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?

[4] Farboodi and Veldkamp (2020) develop a theory of the effect of growth in financial data technology that upends common wisdom.

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.[5] 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. 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, Nosal, and Sundaresan (2020). Kacperczyk, Van Nieuwerburgh, and Veldkamp (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 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, Richmond, and Yogo (2020), and Jiang, Richmond, and Zhang (2020) also apply this approach. Balasubramaniam, Campbell, Ramadorai, and Ranish (2021) estimate a factor model of portfolio holdings. Dou, Kogan, and Wu (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 port-

[5] Coles, Heath, and Ringgenberg (2022) show that an increase in passive investing does not affect price informativeness in this baseline model.

folio 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, Pedersen, and Poteshman (2009)), currency markets (Gabaix and Maggiori (2015), Greenwood et al. (2019), Gourinchas, Ray, and Vayanos (2019)), or corporate bonds (Haddad, Moreira, and Muir (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, Hong, and Liskovich (2014) or Ben-David, Franzoni, and Moussawi (2018). Sammon (2021) studies the response of stock prices around earnings announcements. Bai, Philippon, and Savov (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 much 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.[6] The elasticity of this demand curve, $\mathcal{E}_i$, determines how aggressive the investor is.[7] 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 $\underline{d}_i$.

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

[6]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.

[7]Similarly Gabaix and Koijen (2020) consider log-linear demand curves around a reference price level.

Table 1. The 2-layer model of investor competition.

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

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.[8] 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

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

arbitrage. We confirm these relations empirically in Section 5.3.2.

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.[9] Investors compete for trading opportunities. 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 extent of strategic substitution in demand elasticities.[10] $\underline{\mathcal{E}}_i$ 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

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

[10] We consider strategic substitutes and complements in the sense of Bulow, Geanakoplos, and Klemperer (1985) and defined in chapter 4 of Veldkamp (2011).

the narrative associated with the view 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. 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.[11] 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.

Next, we show how the degree of strategic response matters 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 crucial 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.

[11]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.

2.3 The effect of a rise in passive investing

Our framework is useful to evaluate 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 degree of strategic response χ determines the answer to this question.

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. They 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 responds again to the response of other active investors, until they reach a new equilibrium.[12] The new aggregate elasticity is:

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

When "financial markets are fiercely competitive," 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? In the estimation of Section 4, we find a level of competition χ of 2. Over the last 20 years, the fraction of active investors has decreased by 30%, so we set $\alpha = 70\%$. This implies that the initial elasticity is multiplied by a factor of

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

$(2+1)/(2+1/(70\%)) = 0.875$. The rise of passive investing leads to a substantial drop in elasticity of 12.5%. This is about half 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 idealized view of "fiercely competitive financial markets."

In Section 4, we fully specify our framework to account for heterogeneity across investors and stocks, and estimate it using portfolio holdings data.[13] This allows us to revisit the question of the rise in passive investing in the context of a realistic quantitative model in Section 5.1.

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 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.[14] 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.[15] 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

[13] 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.

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

[15] Formally this corresponds to

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

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 investors 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, Lustig, and Zhang (2017) also emphasize this role of investor competition in markets for complex assets such as mortgage-backed securities. Siriwardane, Sunderam, and Wallen (2021) document many situations in which shocks to one intermediary are imperfectly compensated by the reaction of other intermediaries.[16]

3 Why Are Financial Markets Not "Fiercely Competitive?"

In the 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 investor competition. We discuss the most prominent ones in this section: costly information acquisition, bounded rationality, liquidity, peer effects, and investment mandates. We show that our 2-layer equilibrium model captures the main insights of these theories in a parsimonious way.

[16]Other examples of large effects of intermediary health in specialized markets include Gabaix, Krishnamurthy, and Vigneron (2007) and Siriwardane (2019).

3.1 Costly information acquisition

A basic idea of how investors compete 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.[17] 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 $\bar{x}$ an exogenous fixed parameter 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 $\mu_i \sim \mathcal{N}(f, \sigma_i^2)$.[18] Obtaining more precise signals is more costly. Each agent can acquire an additional private signal $\eta_i \sim \mathcal{N}(f, \sigma_{i,\eta}^2)$ at monetary cost $c_i(\sigma_{i,\eta}^{-2} + \sigma_i^{-2})$, with $c_i(.)$ a non-decreasing positive function.[19] 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: $d_i = \underline{d}_i - \mathcal{E}_i p$.[20] The slope of the demand curve characterizes how aggressively an investor changes her portfolio when the price moves.

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

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

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

[20] 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.

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 and compete with others.

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 information 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: $\chi = -\partial\mathcal{E}_i/\partial\mathcal{E}_{agg}$.[21] 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.[22]

3.2 Other impediments to adjusting elasticity

For this first approach, we saw that the costs of adjusting information strategies limit the ability of investors to compete with each other. Other practical reasons hinder flexibility in setting a trading strategy, and bring χ down towards zero.

One such aspect is risk. Following an aggressive high-elasticity trading strategy entails taking more extreme positions, and hence more risk. Risk itself is endogenous to the aggressiveness of other traders: in more efficient markets, prices are tightly related to fundamentals, while without any active traders, prices are more sensitive to the whims of noise traders.[23] Thus, it is unappealing to follow aggressive strategies exactly when they are most needed, which limits the process of investor competition. In Appendix Section C.1, we present a

[21] 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 $\underline{\mathcal{E}}_{0,i}$.

[22] Coles, Heath, and Ringgenberg (2022) show a full degree of strategic substitution in the baseline setup of Grossman and Stiglitz (1980) without adjustment costs.

[23] De Long et al. (1990) first highlighted the importance of endogenous risk for dynamic arbitrage.

setting where investors do not make information choices but learn from prices. We show that endogenous risk shapes strategic responses; for example when all risk is endogenous investors do not interact, $\chi = 0$, while otherwise there is a positive response.[24]

Another aspect is institutional. Many financial institutions face strong mandates from their ultimate investors in terms of what strategies they are allowed to follow. While these restrictions can be viewed as an optimal contract solving information asymmetry between final investors and the asset manager, they inhibit strategic responses. Investment mandates limit the ability of institutions to react to changes in the behavior of other investors, pushing χ down relative to an unconstrained setting. Beber et al. (2018) show how explicit mandates and constraints in active mutual funds prospectuses strongly limit their investment opportunity set. Investment strategies of banks and insurance companies are also restricted, this time by their regulatory framework (for example, Basel III capital regulation).

Similarly, asset managers might have different incentives than that of their investors which pushes their decisions away from maximizing risk-adjusted returns. For example, Chevalier and Ellison (1997) show that flow-performance sensitivity distorts mutual funds' investment choices.

3.3 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

[24]In the first case, the model coincides with that of the previous section when the information cost is infinitely steep, $c_i''/c_i'^2 \to \infty$.

investors can follow exactly the optimal policies in frictionless models.

First, the information available to investors about the aggregate elasticity might be imperfect.[25] 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.3 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, Rabin, and Vayanos (2019), Bastianello and Fontanier (2021)). 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 passive

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

investing. We show in Appendix C.4 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.

3.4 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.2, we show that a model of market power in the style of Kyle (1989) yields a negative value of χ.[26] 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).

[26] We also show that the measure of price impact Kyle's λ is closely related to the inverse of aggregate elasticity.

Strategic complementarities can also arise through social interactions. When investors follow their peers, as in Hong, Kubik, and Stein (2004), changes in some investors are amplified by similar decisions from other investors.[27] 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.[28] 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

[27] Hirshleifer (2020) more broadly emphasizes the importance of social interactions in finance.

[28] Appendix D.4 details the empirical definition of the outside asset.

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 $\underline{d}_{ik} = \underline{d}_{0i} + \underline{d}'_{1i} X_k^{(d)} + \epsilon_{ik}$ and the baseline elasticity as $\underline{\mathcal{E}}_{ik} = \underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k^{(e)}$, where the two vectors of characteristics are $X_k^{(d)}$ and $X_k^{(e)}$. We also account for 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.

Finally, we estimate the model separately each time period using information only from the cross-section. Thus, we allow all quantities and parameters of the model to depend on time. For ease of notation we drop the subscript t. Putting it all together, our model of portfolio demand is[29]

$$\log \frac{w_{ik}}{w_{i0}} - p_k = \underline{d}_{0i} + \underline{d}'_{1i} X_k^{(d)} - \mathcal{E}_{ik}\ p_k + \epsilon_{ik}, \tag{13}$$

$$\mathcal{E}_{ik} = \underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k^{(e)} - \chi\ \mathcal{E}_{agg,k}. \tag{14}$$

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

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

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

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.[30] This corresponds to setting $\underline{\mathcal{E}}_{1i} = 0$ and $\chi = 0$. Therefore, their model implicitly assumes no strategic response.

[29]To match equation (13) with equation (1), recall that: $d_{ik} = \log \frac{A_i w_{ik}}{P_k}$. Then $\underline{d}_{ik} = \underline{d}_{0i} + \underline{d}'_{1i} X_k + \log(A_i) + \log(w_{0i}) + \epsilon_{ik}$.

[30]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 standard 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 $\mathcal{E}_{ik} = 0$. 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.

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 file with COMPUSTAT for balance sheet information and compute additional stock-level characteristics: book equity, profitability, and investment.

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, Conlon, and Sinkinson (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. Appendix D provides additional details.

4.3 Identification

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

4.3.1 Identifying demand

Combining equation (13) and (14), the model is similar to a regression equation:

$$\log \frac{w_{ik}}{w_{i0}} - p_k = \underline{d}_{0i} + \underline{d}'_{1it} X_k^{(d)} - \left(\underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k^{(e)} - \chi \, \mathcal{E}_{agg,k} \right) \; p_k + \epsilon_{ik}. \tag{19}$$

The parameters are $\underline{d}_{0i}$, $\underline{d}_{1i}$, $\underline{\mathcal{E}}_{0i}$, $\underline{\mathcal{E}}_{1i}$, and χ. There are two challenges to identify these parameters: residual demand ϵ_{ik} is unobservable and aggregate elasticities $\mathcal{E}_{agg,k}$ are themselves functions of $\underline{\mathcal{E}}_i$ and w_{ik} as expressed in the equilibrium condition (18). We make identification assumptions to solve these issues.

As a motivation, consider the simplest possible assumption that takes residual demand as exogenous to all other variables to get the moment condition

$$\mathbf{E}\left[\epsilon_{ik}|X_k^{(d)}, X_k^{(e)}, p_k, \mathcal{E}_{agg,k}\right] = 0. \tag{20}$$

Then, we could estimate (19) 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 — see the equilibrium conditions in equations (17) and (18). Both of these last assumptions are not likely to hold for institutional investors. Therefore we relax these assumptions and propose an alternative identification strategy.

We assume that the variation in total assets and the investment universe is exogenous to the residual demand, an assumption shared with Koijen and Yogo (2019). They argue that the investment universe is often determined by mandates, which are predetermined rules on which assets can be held. Similarly assets under management (AUM) are also predetermined.

Building on this, we construct instruments for equilibrium outcomes p_k and $\mathcal{E}_{agg,k}$. The instrument for the price of asset k follows Koijen and Yogo (2019); define

$$\hat{p}_{k,i} = \log\left(\sum_{j\neq i} A_j \frac{\mathbf{1}_{k\in\mathcal{K}_j}}{|\mathcal{K}_j|}\right), \tag{21}$$

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.[31] Variation in the instrument comes from variation across investors' investment universes. 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.

[31] We consider an alternative with portfolio weights proportional to book equity.

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:

$$\hat{\mathcal{E}}_{agg,k} = \frac{1}{1+\chi|Active_k|} \frac{\sum_{j\in Active_k} A_j/|\mathcal{K}_j| \cdot \mathbf{1}_{k\in\mathcal{K}_j} \cdot \underline{\mathcal{E}}_{jk}}{\sum_{j\in Active_k} A_j/|\mathcal{K}_j| \cdot \mathbf{1}_{k\in\mathcal{K}_j}}. \tag{22}$$

This 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.[32] 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 (19)). To isolate this interaction from linear effects, we also include a linear control for aggregate elasticity, similarly to $X_k^{(d)}$.[33]

The two instruments allow us to weaken the moment condition (20) to

$$\mathbf{E}\left[\epsilon_{ik}|X_k^{(d)}, X_k^{(e)}, \hat{p}_{i,k}, \hat{\mathcal{E}}_{agg,k}\right] = 0. \tag{23}$$

The instrument for the aggregate elasticity 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. Appendix Section E.1 lists the unconditional moments derived from condi-

[32]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:

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

[33]To maintain tractability in estimation we assume that the coefficient on this linear control, like χ, is constant across investors. See Appendix Section E.3.

tion (23) 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 1 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.[34]

4.3.2 The reflection problem

While our instruments provide us with as many moment conditions as parameters, we discuss how the estimation can disentangle the individual component of elasticity from strategic responses. Individual investor elasticities $\mathcal{E}_{ik}$ depend on an investor-specific term, $\underline{\mathcal{E}}_{ik}$, and on the aggregate elasticity $\mathcal{E}_{agg,k}$:

$$\mathcal{E}_{ik} = \underline{\mathcal{E}}_{ik} - \chi \mathcal{E}_{agg,k}. \tag{24}$$

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).

[34]Appendix Figure IA.6 reports similar results for the book-equity weighted instrument.

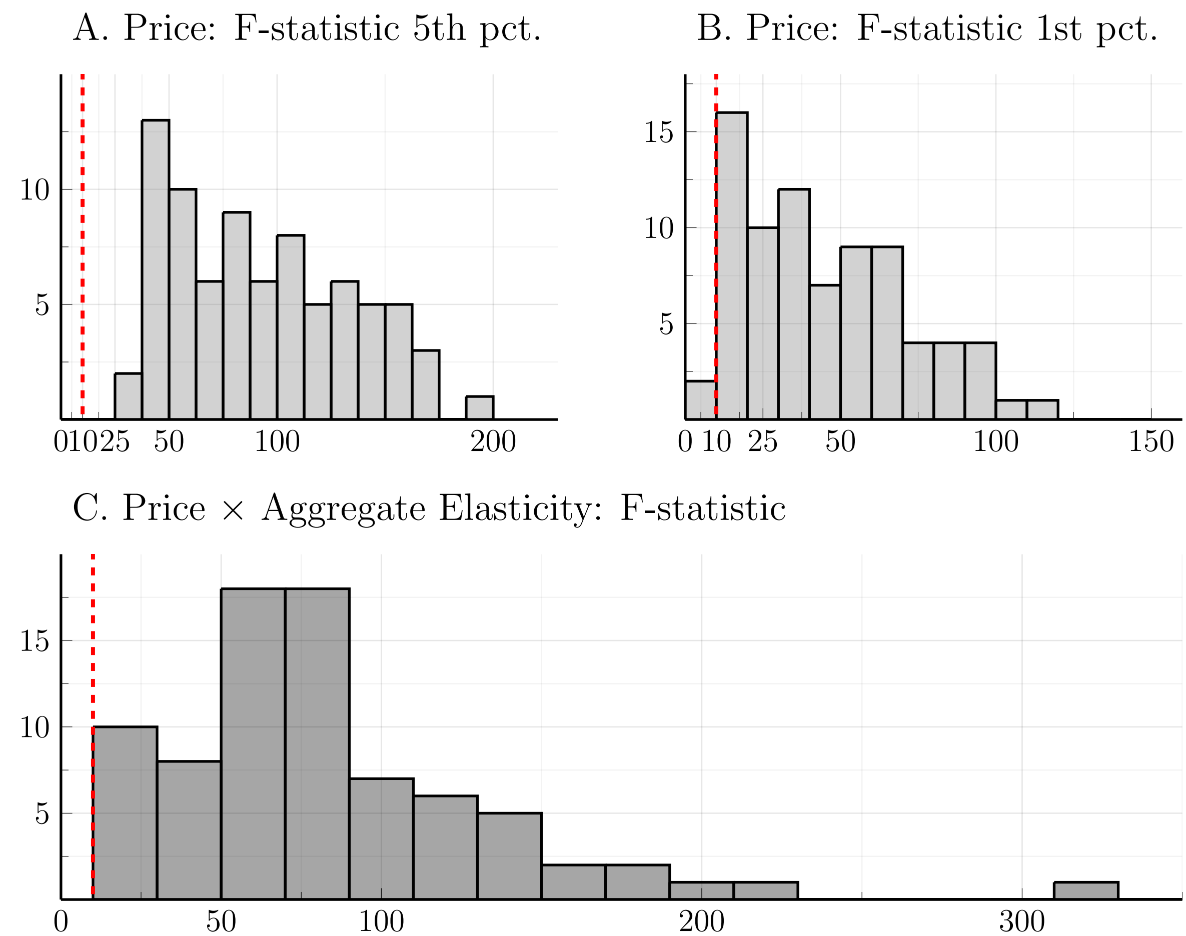

Figure 1. Relevance condition for the price and elasticity instruments. Figure 1 shows the F-statistic of the first-stage regression for the price and aggregate elasticity variables. For the price, we estimate the F-statistic (Kleibergen-Paap) at the manager level for each year. We summarize these statistics 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.

Two features of our model let us solve the reflection problem. First, there is variation in investor composition across stocks, $\mathcal{K}_i$. Second, we assume that the investor-specific component of elasticity depends on observable asset characteristics, $\underline{\mathcal{E}}_{ik} = \underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}_{1i}' X_k$. To measure the effect of competition, the ideal experiment would be to compare the behavior of the same investor for the same stock with variation in the characteristics of the other investors.

With the second assumption, two stocks with the same characteristics X_k elicit the same

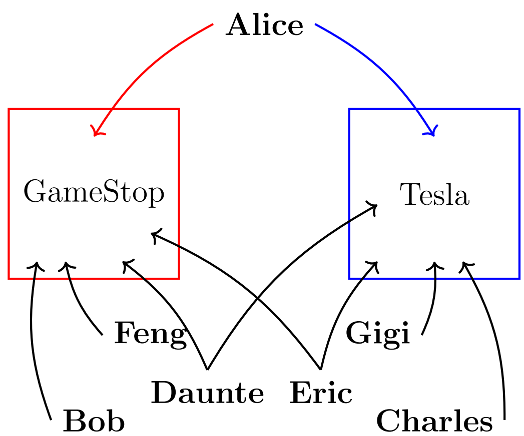

Figure 2. Illustration of identification strategy.

baseline elasticity $\underline{\mathcal{E}}_{ik}$ for the same investor. Furthermore, because the coefficients on stock characteristics are investor specific, we focus on variation within the same investor across different stocks. Finally, to estimate χ, we need variation in $\mathcal{E}_{agg,k}$ across stocks. The different investment universes for different investors guarantee such a source of variation—remember the instrument from equation (22). Figure 2 illustrates this idea: we need to compare how Alice trades differently when facing different groups of other investors, such as for GameStop and Tesla. Last, we need to ensure that the system of equations for all investors and stocks given by (24) and the equilibrium condition for aggregate elasticity (18) has a unique solution. In our example, to estimate Alice's behavior, we simultaneously need to figure out the elasticity for Bob, Charles, Daunte, etc. The following theorem formalizes the intuition behind the needed identifying variation and proves uniqueness. For simplicity of exposition, we focus on the case of constant individual-specific component $\underline{\mathcal{E}}_{ik} = \underline{\mathcal{E}}_i$.

Theorem 1. *A decomposition of demand elasticities $\{\mathcal{E}_{ik}\}_{i,k}$ into individual elasticities $\{\underline{\mathcal{E}}_i\}_i$ and the competition parameter 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 $\sum_{i \in I_k} w_{ik}/P_k A_i \underline{\mathcal{E}}_i \neq \sum_{i \in I_{k'}} w_{ik'}/P_{k'} A_i \underline{\mathcal{E}}_i$.

We derive and discuss this theorem 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 elasticities from χ, it is important to remember that it does not dispense from finding independent variation. Specifically, the instrument for $\mathcal{E}_{agg,k}$ circumvents the issue that investor composition—the portfolio shares in point (b) of Theorem 1—is endogenous.

4.3.3 Implementation

Last, we need to implement the estimation free of the identification issues discussed above. We cannot estimate (19) 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: estimating the model for a given quarter takes about two minutes on a personal computer. The basic idea of our method is to focus on two nested equilibrium questions. On the one hand, if one knows the coefficient on aggregate elasticity, solving the values of aggregate elasticities can be done using an iteration process: run standard instrumental regressions at the investor level to estimate their demand, then update aggregate elasticities using equation (18); repeat until obtaining convergence. On the other hand, if one knows all the equilibrium quantities, finding the coefficient on aggregate elasticity is a low-dimensional fixed point problem involving a single large panel regression; we solve it using the standard Newton method. Appendix Section E.3 details this estimation procedure.

4.4 Estimates

We estimate the model for each quarter from 2001Q1 to 2020Q4. Recall that our identification comes from the cross-section, such that the model is estimated independently for each time period.

4.4.1 Degree of strategic response χ

The average value of the degree of strategic response is $\chi = 2.2$. We show a summary of the estimates of the parameter χ across quarters in row 1 of Table 2; Appendix Figure IA.3 represents the whole distribution. The estimates show little variation around their median. There are no detectable trends in the time series of the estimates as seen in Appendix Figure IA.4.

A degree of strategic response of 2.2 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 2.2. However, this estimate of χ points to an equilibrium behavior far from the standard view. Recall that the "fiercely competitive markets" benchmark corresponds to $\chi \to +\infty$ and the no-strategic-response benchmark to $\chi = 0$. 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 estimate of 2.2, and actually than all of our estimates. We investigate the quantitative implications of our value of χ for the impact of the rise of passive investing in Section 5.

Robustness. We assess the robustness of the estimates along several dimensions. Table 2 reports the results of the estimation for these alternative specifications in rows 2 to 7. Overall, the estimates of competition χ do not vary substantially across specifications — the median value of χ across quarters is always between 1.91 and 2.51.

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

	Estimates for χ		
	Median	25th pct.	75th pct.
(1) Baseline Specification	2.15	1.81	2.76
(2) BE-weighted Instrument for $\mathcal{E}_{agg}$	1.91	1.52	2.31
(3) Additional Controls	2.51	2.09	3.5
(4) AUM-weighted Regression	2.3	1.81	2.8
(5) Book-weighted Regression	2.27	1.76	2.78
(6) Investor-Type Grouping	2.42	1.93	2.94
(7) Constant χ	1.95		
(8) No Instrument for $\mathcal{E}_{agg}$	1.21	0.77	1.56
(9) No Instruments	0.96	0.67	1.38

Table 2 presents statistics of estimates of χ across dates (2001Q1–2020Q4) under various specifications. Our baseline specification (1) estimates χ given aggregate elasticities $\mathcal{E}_{agg,k}$ each period via the regression:

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

where $X_k^{(d)}$ contains log book equity and log book equity squared. $X_k^{(e)}$ is 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. The regression is weighted such that each group's weights sum to the same constant. Specification (2) shows estimates of χ based on the book-equity weighted instrument. Specification (3) adds additional characteristics to $X_k^{(d)}$; profitability, investment and dividends relative to book equity. Specification (4) value-weights the regression by weighting investors by their AUM. Specification (5) similarly value-weights the regression by weighting investors by their book assets. Specification (6) groups investors both by investor type and AUM. Institutional investors whose type we cannot determine are bundled together in a separate group. Specification (7) imposes for χ to be constant across time in the estimation, with each year receiving equal weight. Specification (8) reports results without instrumenting for the aggregate elasticity $\mathcal{E}_{agg}$. Specification (9) additionally removes the instrument for prices.

First, in row 2, we consider 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 a median χ of 1.91, close to our baseline. Row 3 includes additional controls for stock characteristics to the regression (X_k): profitability, investment, and dividend yield. The estimates do not change much. However, we find that including many additional parameters sometimes hinders the convergence of the estimation algorithm (Appendix Table IA.1 restricts to a sample where all the methods converge, 2003Q3 to 2020Q4, and finds very similar results). Rows 4 and 5 consider an alternative weighting scheme. In our baseline, all investors contribute equally to the estimate of χ, while row 4 weighs them by their assets under management. Therefore, if our model was misspecified and the competitive response varied by investor size, this change would lead to different estimates. This is not the case here, with extremely close estimates, suggesting that we capture the empirically relevant moment for the rise in passive investing. Row 5 weighs by book assets under management to avoid contamination by prices, also leading to virtually identical estimates. Row 6 addresses the details of how we deal with investors with few positions. 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.[35] A finer way to construct these groups is to make them based on investor types, but data coverage is incomplete. The estimates in row 6 updates our estimation based on these data, which results in little change. Finally, row 7 constrains the degree of strategic response χ to be constant over time. This pooled estimation is more computationally demanding. It yields a value of χ of 1.95, close to the baseline.

We also estimate the model without using instruments. Row 8 removes the instrument for aggregate elasticity. In this case we find an average value of χ of 1.21. This estimate, far below that from any other specification, suggests 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 9 — leads to even lower estimates, suggesting a deeper bias.

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

4.4.2 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 $\chi = 0$. 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 0.45. This magnitude is far from the asset-pricing benchmark of perfectly horizontal demand curves with infinite elasticity.[36] However, it is consistent with other empirical estimates, in particular based on portfolio data; see for example the discussion in Chang, Hong, and Liskovich (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 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 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

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

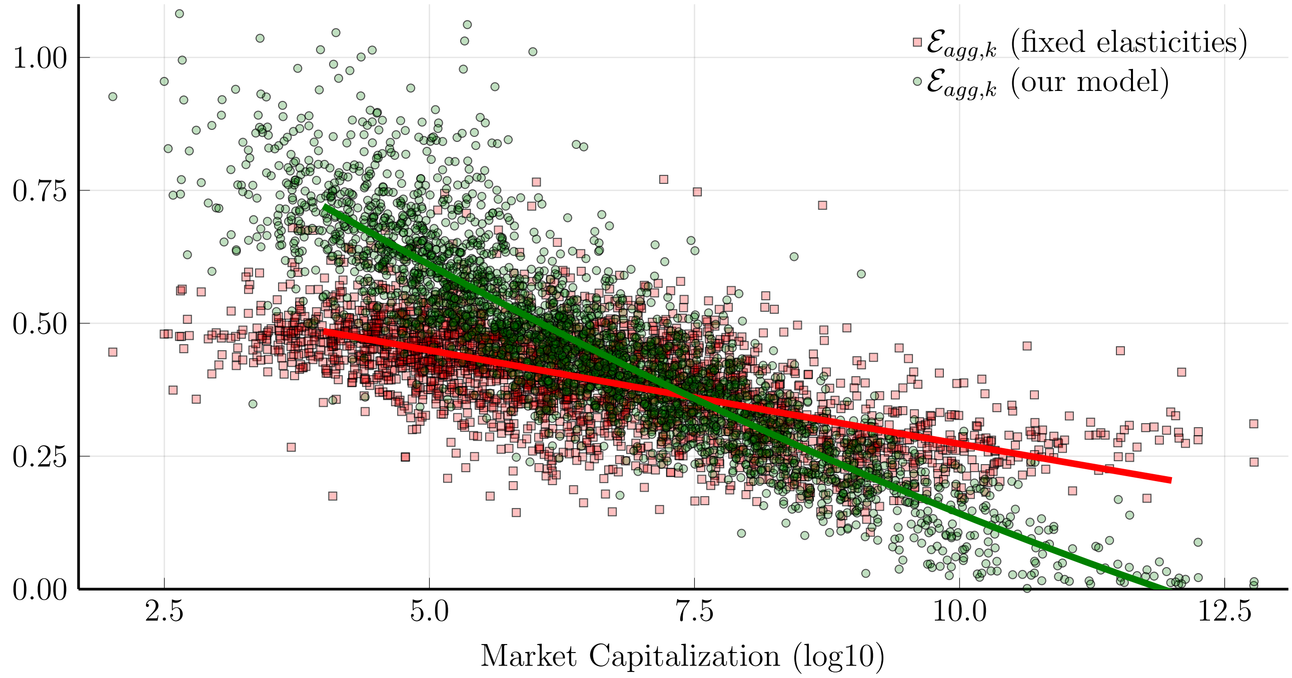

Figure 3. Aggregate elasticity at the stock level: $\mathcal{E}_{agg,k}$. Figure 3 represents estimates of the aggregate elasticity $\mathcal{E}_{agg,k}$ as a function of their market capitalization (in logarithm) for the date 2011Q3. Each point represents a stock; green circles are our estimates, while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

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%.

The negative relation between size and elasticity might appear surprising given existing evidence suggesting that large stocks are more informationally efficient.[37] However, there

[37]See Lo and MacKinlay (1990), Jegadeesh and Titman (1993), Lakonishok, Shleifer, and Vishny (1994),

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

	Panel A: Statistics of average elasticity across stocks			
	Average	25th pct.	Median	75th pct.
Elasticity $\mathcal{E}_{agg}$	0.489	0.411	0.46	0.54
Fixed elasticity	0.389	0.357	0.389	0.442
	Panel B: Regression coefficient (by dates) of elasticity on size			
	Average	25th pct.	Median	75th pct.
Elasticity $\mathcal{E}_{agg}$	-0.109	-0.117	-0.1	-0.0855
Fixed elasticity	-0.0286	-0.0309	-0.0272	-0.0249
	Panel C: Residual cross-sectional standard deviation of elasticity			
	Average	25th pct.	Median	75th pct.
Elasticity $\mathcal{E}_{agg}$	0.0498	0.0389	0.0441	0.0521
Fixed elasticity	0.0842	0.0739	0.0826	0.0917

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.

are good reasons 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.[38] 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 F details this

and Hong, Lim, and Stein (2000).

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

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.[39]

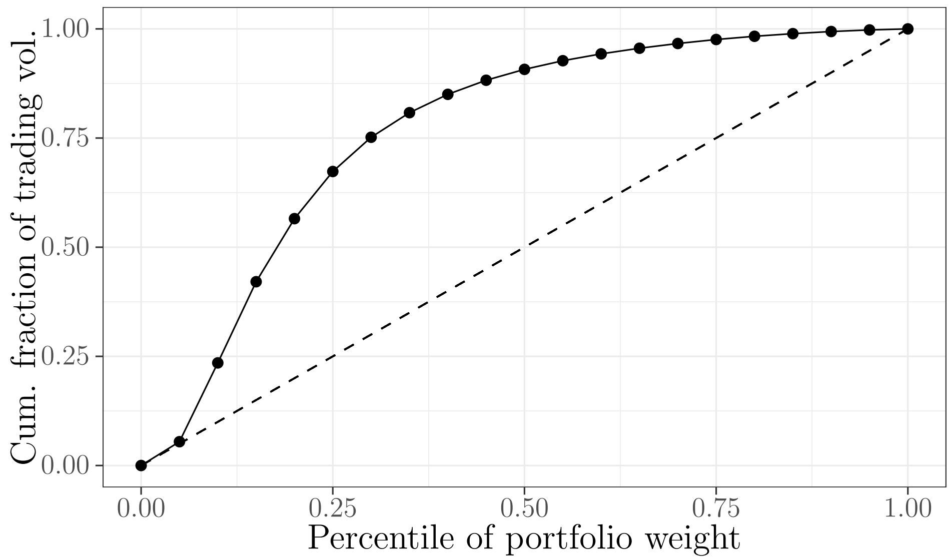

Figure 4. Trading activity across portfolio positions. Figure 4 presents the cumulative share of trading activity (defined in equation (IA.153)) by quantiles of investor portfolio weights. The dashed line is the 45 degree line.

5 Implications

5.1 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. We update and confirm these trends in Figure 5. The share of passive funds of the

[39]In the model of Section 3, both elasticity and the quantity of noise trading determine price informativeness. Farboodi et al. (2021) use a richer structural model to decompose informativeness into data, growth, and volatility.

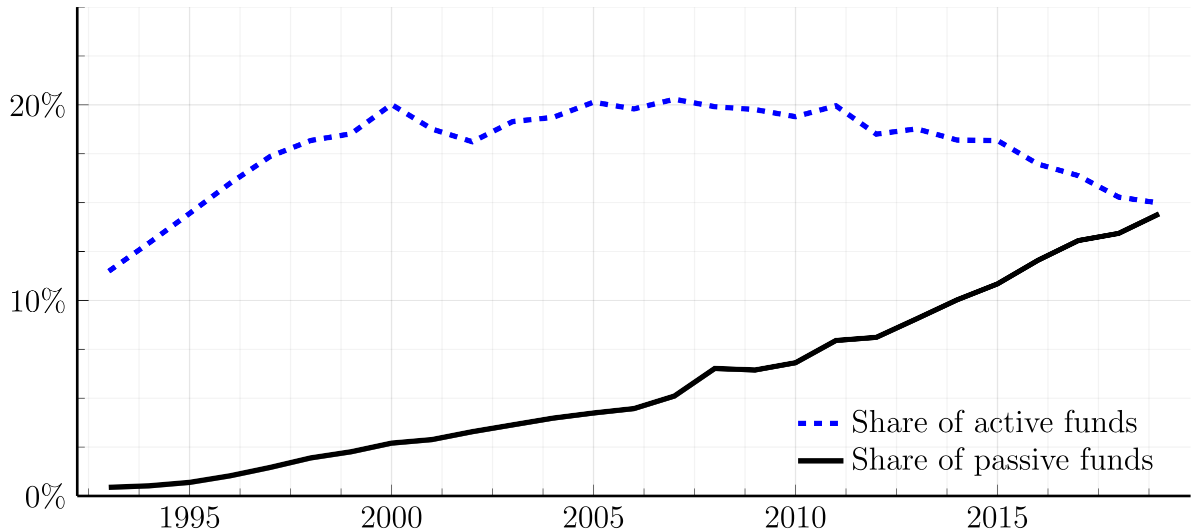

Figure 5. Share of passive and active funds. Figure 5 shows the share of domestic mutual funds and ETFs as a fraction of the US stock market capitalization for passive funds (black solid line) and active funds (blue dashed line). Source: ICI (2020).

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.[40] Our model takes a more comprehensive view of who are the passive investors, not restricting ourselves to mutual funds.[41] With this approach we find that the share of passive strategies has grown by 22 percentage points over the last 20 years (see Appendix Figure IA.8).

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 standard 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.

[40]We report the dollar numbers in Figure IA.7. 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.

[41]Our methodology for measuring passive investing as inelastic demand is described further in Appendix D.3.

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.[42] 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

$$\mathcal{E}_{agg,k} = |Active_k| \times \left(\sum_{i \in Active_k} \frac{w_{ik} A_i}{\sum_{j \in Active_k} w_{jk} A_j} \cdot \underline{\mathcal{E}}_{ik} - \chi \mathcal{E}_{agg,k} \right) \tag{25}$$

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.[43]

From this expression we obtain the effect of a change in the fraction of active investing.

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

[43]Using equation (25), we can solve for the equilibrium value of aggregate elasticity

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

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:

$$\frac{d \log \mathcal{E}_{agg,k}}{d \log |Active_k|} = \frac{1}{1 + \chi \ |Active_k|}. \tag{26}$$

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.[44] When χ is large, 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 competition parameter and found that $\chi = 2.15$. 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, $\chi = 2.15$, we find a value of the pass-through of[45]

$$\frac{1}{1 + \chi \ |Active_k|} = \frac{1}{1 + 2.15 \times 0.68} = 40.6\%. \tag{27}$$

This implies that the strategic response is strong enough to compensate about 60% of the

[44]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.

[45]When the share of active investors is at 81% as in 2001 the pass-through is 36.5%, while when this share is at its lowest value of 59% at the end of the sample it is 44%.

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 $40.6\% \times 32\% = 13\%$. Translating the elasticities into price multipliers, this implies that the price impact of buying \$1 of a stock went up roughly from \$2.5 to \$2.9. 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 19% drop in the total fraction of active investors. With our pass-through of 0.4, this increase in passive investing by mutual funds reduces elasticities by 8%.

5.2 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.

5.2.1 The downward trend in 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, $\mathcal{E}_{agg,k}$. We find a downward trend in equilibrium elasticities across the whole distribution of stocks. The average elasticity (bold solid line) goes from 0.46 to 0.31, a 33% drop. The one exception to the trend is the early part of the sample with an increase in elasticities between 2000 and 2004. The tails of the distribution also decrease. The 90th percentile (upper dashed line) drops from 0.64 to 0.53. The 10th percentile (lower dashed line) also drops from 0.25 to 0.12.

We further our understanding of what is behind this pervasive decline in the next section through a simple decomposition.

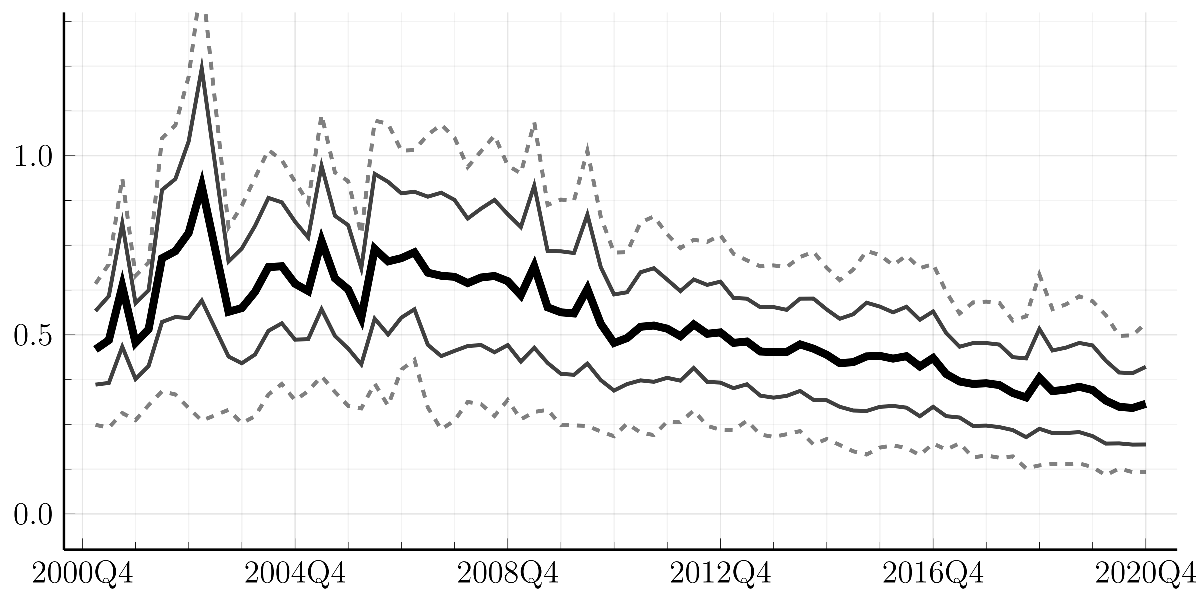

Figure 6. Distribution of aggregate elasticity across stocks. Figure 6 traces out the distribution of aggregate elasticity $\mathcal{E}_{agg,k}$ over time. The bold line represents the average elasticity across stocks for each year. The solid lines represents the 25th and 75th percentile and the dashed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

5.2.2 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 is purely cross-sectional, we can use the time-series dimension of our estimates as a description of the evolution of the demand for stocks over time. To make parameters such as the investor-specific demand elasticity $\underline{\mathcal{E}}_i$ comparable across periods, we use the model estimates under the assumption that the degree of strategic response is constant over time at its sample median of 2.15.

We decompose changes in elasticity from year to year into three components by differentiating equation (25). 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 (25). We derive the effect of a change in investor composition,

$$\underbrace{\frac{d\mathcal{E}_{agg,k}}{\mathcal{E}_{agg,k}}}_{\text{Change in aggregate elasticity}} = \underbrace{\frac{d|Active_k|}{|Active_k|}}_{\text{Share of active investors}} + \underbrace{|Active_k| \cdot \frac{d\langle\underline{\mathcal{E}_{ik}}\rangle}{\mathcal{E}_{agg}}}_{\text{Individual elasticity of active investors}} \\ \underbrace{- \chi|Active_k|\frac{d\mathcal{E}_{agg}}{\mathcal{E}_{agg}}}_{\text{Strategic response}}. \tag{28}$$

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.

We accumulate the three terms of this decomposition over time in Figure 7 and we summarize the total effects in Table 4.[46] We smooth the series to make the secular trends easier to identify. Recall that aggregate stock-level elasticity has decreased by 33% on average (Figure 6). Consistent with the importance of the rise in passive investing discussed in Section 5.1, we find that the direct effect of the decrease in the fraction of active investors contributes 77% of this total drop in elasticity. Interestingly, investors also change their own elasticities at the intensive margin. While individual elasticities increase until 2006, they experience a sharp drop after and contribute a 39% decline overall.[47] Appendix Figure IA.9 confirms this pattern holds in the entire cross-section of investors. This second direct force adds 119% to the drop in aggregate elasticities. However, the strategic response strongly

[46]Because we cannot continuously integrate equation (28), we use the natural discrete approximation of the first and third terrms and compute the second one as a residual.

[47]Relatedly, Pavlova and Sikorskaya (Forthcoming) documents a trend down in the tracking error of active mutual funds.

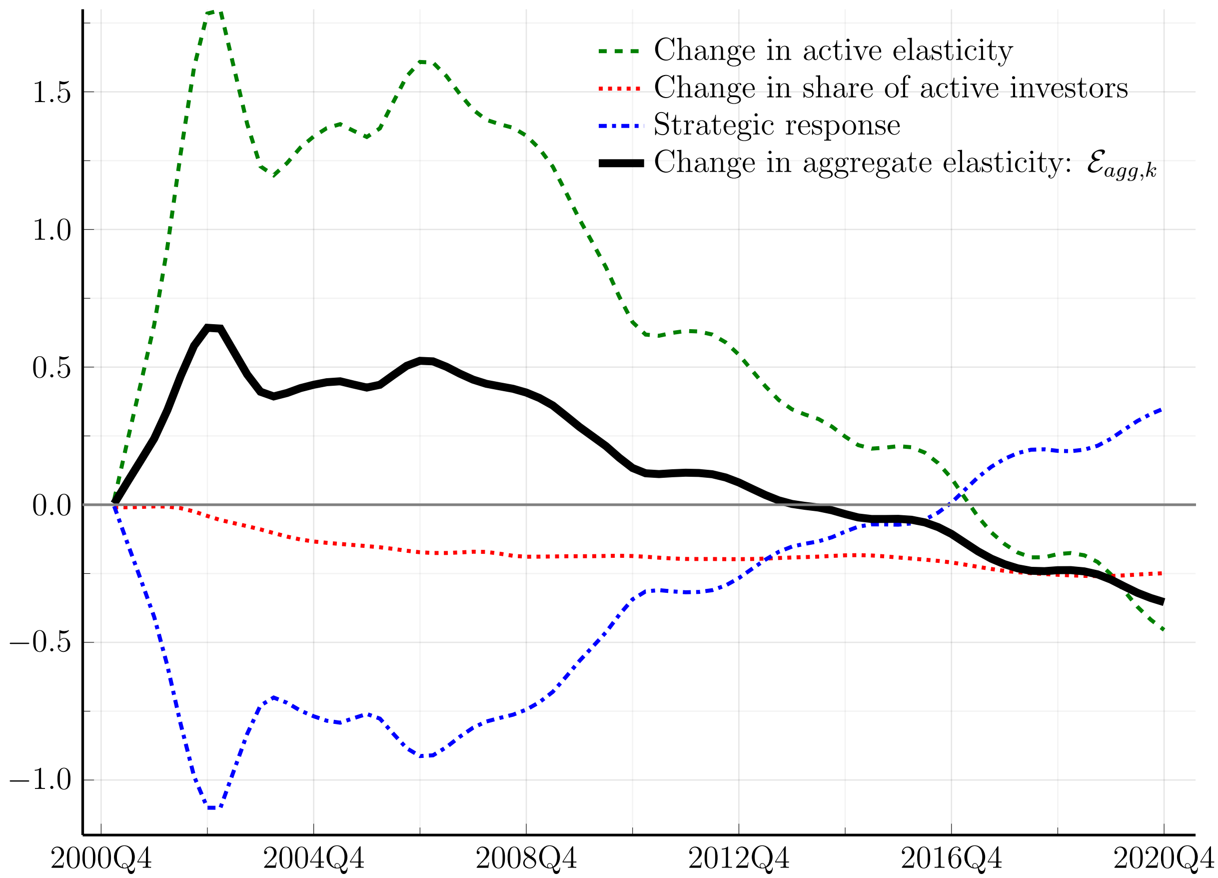

Figure 7. Decomposition of the change in aggregate elasticity. Figure 7 shows the decomposition derived in equation (28) over time. We compute each term of the decomposition for each date and accumulate the changes over time, scaled by the initial aggregate elasticity.

mitigates these individual changes in equilibrium. The strategic response reverses around half of the decline, leading to the total change in aggregate elasticity of −33%.

5.2.3 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, $\underline{\mathcal{E}}_{ik}$,

Table 4. Decomposition of the change in aggregate elasticity $\mathcal{E}_{agg}$

Aggregate elasticity	Decomposition		
Total change (2001-2020)	Active share	Active elasticity	Competition
−33%	77%	119%	−96%

Table 4 reports the total change in aggregate elasticity and its decomposition, as derived in equation (28). We compute each term of the decomposition for each date and accumulate the changes over time. We report each term as a fraction of the total change in elasticity.

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 of "fiercely competitive investors," 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 decline 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

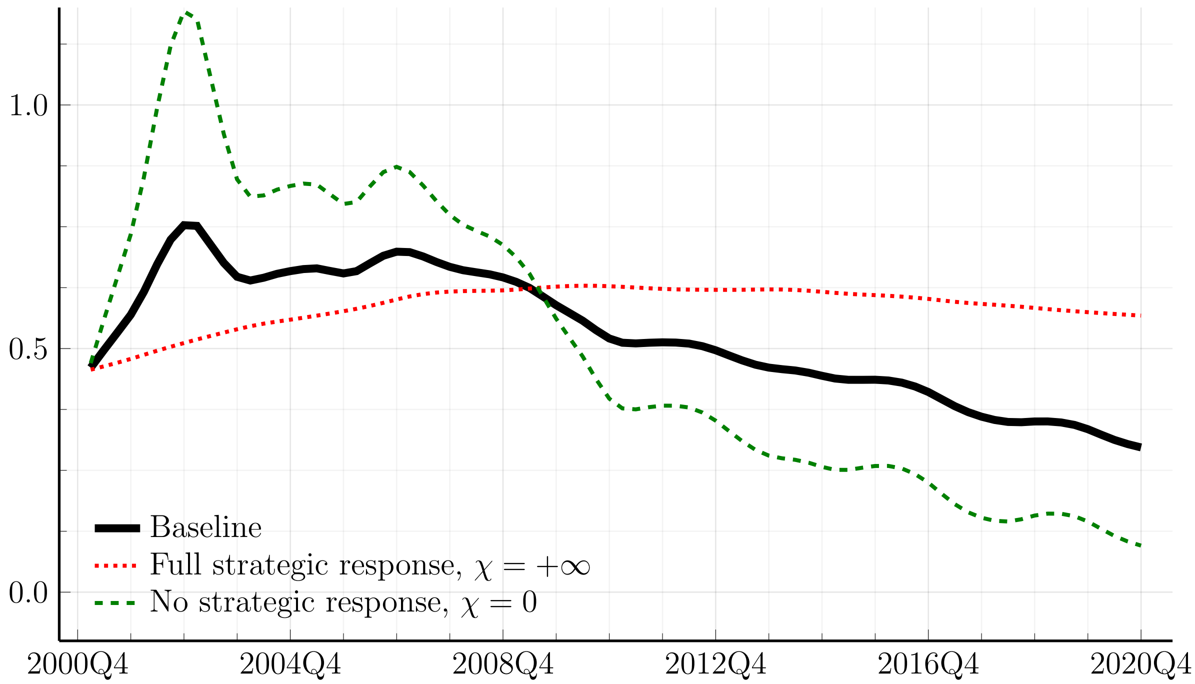

Figure 8. The evolution of aggregate elasticity under alternative competition regimes. Figure 8 shows the evolution of aggregate elasticity $\mathcal{E}_{agg,k}$ under alternative strategic regimes. The bold black line presents our baseline estimate. The dotted red line shows the elasticity with strong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

of a downward trend in aggregate elasticities.

5.3 Implications in the cross-section of stocks

5.3.1 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 that driving our baseline estimates (the ones caused by our instrument).

We regress annual log changes in stock-level elasticity on changes in the fraction of active investors:

$$\log(\mathcal{E}_{agg,k,t}) - \log(\mathcal{E}_{agg,k,t-1}) = \beta \left(\log(|Active_{k,t}|) - \log(|Active_{k,t-1}|)\right) + \alpha_k + \gamma_t + e_{k,t}. \quad (29)$$

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 (26), about 0.4. 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 5 presents the result, using the unconstrained cross-sectional model estimates. Column 1 is a univariate regression; columns 2 and 3 add date then stock fixed effects. Throughout, we find a coefficient of about 0.4, close to the theoretical pass-through.[48] 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. Furthermore, because our model estimates are only based on cross-sectional evidence, this result from including the time series dimension provides additional support for our theory. Going in this direction, in Appendix Table IA.3, we confirm that the regression results are mostly unchanged when using the estimates that impose a constant value of χ through time.

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

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

Table 5. Change in aggregate stock-level elasticity $\mathcal{E}_{agg,k}$ on the active share

	Change in Elasticity				
	(1)	(2)	(3)	(4)	(5)
Change in Active share	0.446***	0.475***	0.457***	0.426***	0.389***
	(0.044)	(0.036)	(0.036)	(0.034)	(0.066)
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	0.076	0.461	0.497	0.569	0.748
First-stage F statistic					9.444
First-stage p value					0.000

Table 5 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 for columns 1-4, and clustered by date for column 5.

change their portfolio after reclassification. Following Chang, Hong, and Liskovich (2014), Ben-David, Franzoni, and Moussawi (2018), and Chinco and Sammon (2022), we exploit the mechanical rule that allocates stocks between the Russell 1000 and 2000 indexes.[49] We use the index-switching event as an instrument for the share of passive investors; column 5 of Table 5 reports the result. The first stage is significant with reclassification changing active ownership by about 5% (see Appendix Table IA.4). The coefficient is 0.39, again very close to the theoretical pass-through.

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

5.3.2 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 many theories. Second, these elasticities are a key determinant of the behavior of asset prices. For example, aggressive investors limit the influence of excess fluctuations in prices, which often results in less volatility or more price informativeness. 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:

$$Y_{k,t} = \beta \mathcal{E}_{agg,k,t} + \gamma_t' X_{k,t} + \alpha_t + e_{k,t}, \tag{30}$$

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 of the stocks. Therefore, our preferred specification is 2SLS in which we instrument for $\mathcal{E}_{agg,k,t}$ using $\hat{\mathcal{E}}_{agg,k,t}$. We have already shown in Section 4.3.1 that the first stage of this estimation is strongly significant.

Table 6 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, Franzoni, and Moussawi (2018) on index inclusions. When a stock has more passive investors following an index switch, its aggregate elasticity declines due to a lack of competition (Table 5), 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). We find no significant relationship. However, the large standard errors reveal that the relation is difficult to estimate precisely rather than a tight zero. 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.

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.

6 Conclusion

The idea that investors compete 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 U.S. 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 60% 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, competition 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 face of institutional investing.

Table 6. 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	0.081	-0.757^{***}	0.008	-0.740^{***}	-0.078	-0.270	1.250^{***}	-0.475^{**}
	(0.068)	(0.164)	(0.049)	(0.134)	(0.306)	(0.731)	(0.066)	(0.228)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	IV	OLS	IV	OLS	IV	OLS	IV
N	219,531	219,531	206,140	206,140	66,677	66,677	216,983	216,983
R^2	0.218	0.178	0.247	0.209	0.020	0.019	0.744	0.610

Table 6 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 (22). 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.

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