The Making of Momentum

A Demand-System Perspective

Abstract

I develop a framework to quantify which features of investors' dynamic trading strategies lead to momentum in equilibrium. I distinguish persistent demand shocks, capturing underreaction, and the term structure of demand elasticities, representing arbitrage intensities decreasing with investor horizon. I introduce both channels into an asset demand system that I estimate from institutional investors' portfolio holdings and prices. Investors respond more to short-term than longer-term price changes: the term structure of elasticities is downward-sloping, creating momentum, whereas demand shocks mean-revert, contributing toward reversal. Stocks with more investors with downward-sloping term structures exhibit stronger momentum returns by 7% per year.

1 Introduction

Momentum, the tendency for past winners to outperform past losers (Jegadeesh and Titman, 1993), is one of the most challenging anomalies to understand in stock returns;[1] it constitutes some of the most suggestive evidence that investors make mistakes and that these mistakes aggregate to affect prices. And while many explanations for momentum have been proposed, tests of these theories have, surprisingly, mainly focused on patterns in returns.[2] In this paper, I take a different approach by looking at the joint behavior of investor portfolio holdings and prices. I propose a framework to measure the dynamic trading strategies of each investor and quantify how they contribute to the making of momentum in equilibrium. Looking jointly at quantities and prices gets to the heart of how momentum is created — investors' dynamic trading — and yields new insights into who are the investors driving momentum.

My first insight is that explanations for momentum can be organized within two broad mechanism: the persistence of demand shocks, representing relative underreaction, and a downward-sloping term structure of demand elasticities, which captures different intensities of arbitrage activity across time horizons. I introduce these mechanisms into an asset demand system in the style of Koijen and Yogo (2019) and estimate it from data on portfolio holdings. My estimates show that equilibrium momentum is primarily the result of the downward-sloping term structure of demand elasticities. Market participants respond more strongly to price changes over the most recent quarter than to longer-term variation over one year.[3] My framework also predicts higher momentum returns in stocks owned by investors with a downward-sloping term structure of elasticities. Accordingly, I sort stocks based on their aggregate term structure of elasticities and find 7% higher momentum returns in stocks where

[1]Fama (2014), in his Nobel Prize Lecture, acknowledges momentum as "the biggest challenge to market efficiency."

[2]Some notable exceptions include early work by Grinblatt, Titman, and Wermers (1995) and Grinblatt and Keloharju (2000) and more recent work by Cremers and Pareek (2015) and Chui, Subrahmanyam, and Titman (2022).

[3]I specifically compare quarterly and yearly horizons to align with the empirical definition of momentum formation periods (e.g., Jegadeesh and Titman, 1993). So when I say that the term structure of elasticities is downward-sloping, I mean that it is downward-sloping at these specific frequencies.

it is more steeply downward-sloping.

Which aspects of how people trade lead to momentum? The first one is, in the language of demand systems, about the persistence of demand shocks. It is the mechanism behind classic momentum explanations through underreaction to information (e.g., Chan, Jegadeesh, and Lakonishok, 1996): Upon receiving fundamental news, investors respond only partially when incorporating it into their demand. Over time, they react more and more strongly to the information, leading to a build-up of demand, thereby creating a drift in prices.[4] This mechanism is about the own, investor-specific partial-equilibrium demand of investors. But there is another potential source of momentum, distinct from underreaction in demand shocks: differences in investors' ability to absorb shocks across horizons, the term structure of demand elasticities. It relates to how investors respond to equilibrium prices across time. For example, consider a hedge fund fire-selling 10 million shares of Apple to meet investor redemptions (and abstract from information effects). Initially, this demand shock is absorbed predominantly by relatively higher-frequency arbitrageurs on the lookout for fast opportunities, so the price of Apple does not decrease much. But higher-frequency traders have short investment horizons and soon turn their attention elsewhere. So they sell their Apple shares to investors with longer horizons, for example, active mutual funds. If the higher-frequency traders are more willing to absorb the Apple shares than the active mutual funds, then the price of Apple stock will decrease further. More generally, when there is a mismatch in the aggregate risk-bearing capacity at the short versus the long horizon — the term structure of demand elasticities — then the equilibrium price impact of a demand shock will increase over time. In other words, when short-run arbitrage exceeds long-run arbitrage, the term structure of demand elasticities is downward-sloping, and momentum arises.

To quantify the importance of these two channels, I incorporate the term structure of elasticities into an asset demand system in the tradition of Koijen and Yogo (2019). Intro-

[4]The literature has put forward many foundations for such underreaction. I use the term "underreaction" in a broad sense to capture relative patterns in beliefs across time, encompassing models of delayed overreaction alongside underreaction stricto sensu. Section 2.5 summarizes these theories and shows how they generate persistence in investor demand.

ducing dynamics into a demand system leads to new challenges for identification, especially in separating the two explanations for momentum. The inclusion of price changes at different horizons creates a dynamic simultaneity problem, resulting from the combination of persistent demand shocks with the classic simultaneity problem of prices and demand. In other words, it is difficult to disentangle the dynamics of demand shocks from the evolution of investors' equilibrium responses to said shocks across time. Starting from the idea of mutual fund flow-induced trading (Lou, 2012) — facing outflows, mutual funds scale down their existing holdings to meet redemptions, thereby putting downward price pressure on the stocks they hold — I show how to construct appropriate instruments for recent and longer-term price changes to overcome the dynamic simultaneity issue. However, the relation between mutual fund flows and past fund returns, retail investors chasing fund performance, threatens exogeneity.[5] To account for it, I orthogonalize mutual-fund flows to past fund returns and past fund flows.

I estimate the model for institutional investors in the U.S. stock market between 1999 and 2020. My estimates suggest that, on average, the term structure of elasticities is downward-sloping: The market is 25% less elastic in its response to price movements over the past year compared to the past quarter. To put this number into context, consider homogenous investors with an elasticity of 4 to returns over the most recent quarter but a lower elasticity of 3 to longer-term variation at the horizon of a year. Here, investors are $(4-3)/4 = 25\%$ less elastic at longer horizons, so the term structure of elasticities is downward-sloping. How does a \$100 inflow affect prices? Initially, the recent elasticity of 4 implies that the extra \$100 raise the value of the stock by $\$100/4 = \$25$. Subsequently, driven by the downward-sloping term structure of elasticities, the price impact rises to $\$25/(1-25\%) \approx \$33$.

There is substantial variation in elasticity estimates across investors. In particular, my estimates identify a group of investors who are very active at a quarterly horizon but less so in the long run. These investors drive much of the overall pattern of downward-sloping term

[5] The flow-performance relation between mutual fund flows and past fund returns was originally documented in Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

structures. And because of cross-sectional variation in how much they own, I find substantial variation in the slope of the aggregate term structure of elasticities across stocks as well. It is more strongly decreasing in stocks that are unprofitable, small, or have a high dividend yield.

A distinct advantage of the demand-system approach is that it is an equilibrium framework. That is, it ensures that observed prices are the equilibrium of the individual behavior of all investors. In particular, this allows me to decompose the observed momentum returns into components representing dynamic trading against prices, the evolution of fundamentals, and persistent demand shocks.

The downward-sloping term structure of elasticities is the primary driver of momentum returns. On its own, this phenomenon would create annualized momentum returns of about 24% between 1999 and 2020. More specifically, if investors had not changed their demand from period to period for any reason other than the term structure of elasticities, then the equilibrium-implied period-to-period price changes would have resulted in annualized momentum returns of 24%. In contrast, investor demand shocks mean-revert, creating reversal rather than momentum.[6] This observation is at odds with theories that generate momentum through underreaction. But it does not mean that underreaction to news does not exist. First, it might have played a less dominant role only recently, which is in line with ideas of momentum anomaly attenuation (Chordia, Subrahmanyam, and Tong, 2014) and the overall poor performance of classic momentum strategies between 1999 and 2020. Second, underreaction might occur under specific conditions. For example, I find that past latent demand predicts future stock fundamentals that enter investors' demand functions, consistent with Novy-Marx (2015).

I use the model estimates to design a demand-system-boosted momentum strategy. In particular, the model predicts larger momentum returns in stocks with steeply downward-sloping term structures of elasticities. Accordingly, I sort stocks into two portfolios based

[6]Similarly, Koijen and Yogo (2019) generate a profitable reversal strategy based on the mean-reversion of demand shocks.

on their term structures of elasticities. Then, within each subset, I examine the returns to a standard momentum strategy that goes long the tercile of past winners and short past losers. While the returns to a conventional momentum strategy were low at an annualized 2% between 1999 and 2020, the returns to momentum among stocks with more steeply decreasing term structures of elasticities were higher by 7% than among stocks with flatter term structures. This difference cannot be attributed to common risk factors, including the momentum factor itself, and is robust to controlling for stock size. Interestingly, momentum among stocks with steeply decreasing term structures avoids momentum crashes that standard momentum strategies experience following stock market crashes (Daniel and Moskowitz, 2016).

My results highlight the importance of incorporating both the persistence of investors' demand shocks and the downward-sloping term structure of demand elasticities into models that generate momentum in equilibrium. Most models focus on the first aspect, which captures underreaction to news by behavioral investors. However, I show this channel to be less important empirically. At the same time, existing models often ignore what my model estimates to be the primary driver of momentum: the term structure of elasticities, representing investors' differential responses to short- and long-term variation in prices. Such dynamic responses to prices could represent frictions rooted in the industrial organization of the financial industry or reflect investors behavioral biases in processing the information contained in equilibrium prices (Bastianello and Fontanier, 2021). They are likely also important for other anomalies based on time-series patterns in prices. For example, my framework can be adapted to study the drivers of price reversals at short horizons below a quarter and long horizons beyond a year.[7] More generally, my framework can also speaks to the role of investor demand in the evolution of fire sales. Does investors' dynamic trading exacerbate or allevi-

[7]The term structure might look different at such different horizons. For example, Duffie (2010) emphasizes the role of financial intermediaries' limited risk-bearing capacity at the time of a shock for the generation of short-term reversal in prices, consistent with an upward-sloping term structure of elasticities at horizons below a quarter. Another example is over-extrapolation of very recent past returns (e.g, Gulen and Woeppel, 2022), which can be represented through an upward-sloping term structure at short horizons.

ate shocks as a fire sale progresses? The answer to this question depends on how investors dynamically respond to prices and can have important financial stability implications.

Contribution to the literature. Momentum, the tendency of past winners to outperform past losers, is one of the most widely studied anomalies (Jegadeesh and Titman, 1993, 2001). It is robust: to different formation-period definitions (Grinblatt and Moskowitz, 2004; Novy-Marx, 2012; Goulding, Harvey, and Mazzoleni, 2022), on industry, style and factor level (Moskowitz and Grinblatt, 1999; Barberis and Shleifer, 2003; Chen and De Bondt, 2004; Ehsani and Linnainmaa, 2022), across asset classes (Asness, Moskowitz, and Pedersen, 2013; Burnside, Eichenbaum, and Rebelo, 2011; Menkhoff et al., 2012), and in the time series (Moskowitz, Ooi, and Pedersen, 2012). Many mechanisms have been proposed, including both rational (Berk, Green, and Naik, 1999; Johnson, 2002; Pastor and Stambaugh, 2003; Sadka, 2006; Vayanos and Woolley, 2013) and behavioral explanations (Long et al., 1990; Chan, Jegadeesh, and Lakonishok, 1996; Daniel, Hirshleifer, and Subrahmanyam, 1998; Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999; Grinblatt and Han, 2005; Daniel, Klos, and Rottke, 2021). The term structure of elasticities is conceptually related to Lou and Polk (2021), who show how momentum can arise from aggregate overreaction by arbitrageurs but use the behavior of prices for measurement. A small number of papers study momentum strategies in the context of mutual funds' or institutional investors' portfolio holdings. For example, Cremers and Pareek (2015) document that momentum is stronger in stocks held by institutions that own shares for a short period of time. Goetzmann and Massa (2002) emphasize the role of fund flows. More recently, Dong, Kang, and Peress (2022) find that persistent but not transient flows to mutual funds predict factor-level returns because fund managers only reinvest persistent flows into factor strategies, generating factor momentum. Grinblatt, Titman, and Wermers (1995) measure that mutual funds, on average, hold past winners. I contribute to this literature by not only measuring dynamic trading strategies for each investor but also aggregating them to create momentum in equilibrium. In this process, I particularly emphasize the role of arbitrage intensities across horizons.

I also contribute to the recent literature on demand systems pioneered by Koijen and Yogo (2019). Demand systems have been used to study the role of investors in the U.S. stock market (Koijen and Yogo, 2019; Koijen, Richmond, and Yogo, 2020; Tamoni, Sokolinski, and Li, 2022), in an international context (Koijen and Yogo, 2020; Jiang, Richmond, and Zhang, 2020, 2022), in government- and corporate bonds (Koijen et al., 2021; Bretscher et al., 2020), and in ESG investing (Noh and Oh, 2020; van der Beck, 2021). Balasubramaniam et al. (2021), Betermier et al. (2022) and Gabaix et al. (2022) focus on the role of households in India, Norway and the United States. Gabaix and Koijen (2020) estimate macro elasticities for the aggregate stock market. Haddad, Huebner, and Loualiche (2022) employ a demand system to study the effects of the rise of passive investing. Similar to van der Beck (2022), I identify institutions' elasticities based on their reactions to shocks from mutual funds' flow-induced trading. As a result, my elasticity estimates are higher than in static demand-based demand models (e.g., Koijen and Yogo, 2019) by a factor of about three, in line with estimates from Pavlova and Sikorskaya (2022). My key innovation to this literature is introducing the term structure of demand elasticities, which I show to be substantially downward-sloping.

Finally, I relate to the literature on segmentation in financial markets (Merton, 1987; Grossman and Miller, 1988; Shleifer and Vishny, 1997; Gromb and Vayanos, 2002; Greenwood, Hanson, and Liao, 2018). Segmentation between market participants occurs in government bonds (Guibaud, Nosbusch, and Vayanos, 2013; Greenwood and Vayanos, 2014), options (Gârleanu, Pedersen, and Poteshman, 2009), currencies (Gabaix and Maggiori, 2015), mortgage-backed securities (Gabaix, Krishnamurthy, and Vigneron, 2007), and credit default swaps (Eisfeldt et al., 2022), all asset classes in which financial intermediaries play a prominent role (Haddad and Muir, 2021). Segmentation is often the result of some form of preferred habitat (e.g., Vayanos and Vila, 2021). Siriwardane, Sunderam, and Wallen (2021) analyze segmentation in the cross-section of arbitrages. Greenwood and Vissing-Jorgensen (2018) and Jansen (2021) emphasize the role of long-term investors in bonds. Lan, Moneta, and Wermers (2015) and Van Binsbergen et al. (2022) document horizon-specific investment skills across mutual funds based on their turnover. I contribute to this literature by emphasizing a related but distinct form of segmentation: differences in arbitrage activity across investment horizons. This is not unlike how short-term reversal is generated through slow-moving capital (Mitchell, Pedersen, and Pulvino, 2007; Duffie, 2010), but at longer-term horizons, creating momentum rather than reversal.

2 Equilibrium Momentum from Dynamic Trading

I present an equilibrium framework for how the evolution of investor demand can lead to momentum. Two distinct mechanisms shape momentum in equilibrium: persistent demand shocks, capturing underreaction to information, and the term structure of demand elasticities representing how investors respond to price changes across horizons. I proceed by first introducing a model that incorporates both mechanisms through flexible but exogenously specified investor decision functions. Then, I show how the model generates momentum as the equilibrium of these investor demands. Finally, I discuss the relation of these two meta-theories of momentum to canonical micro-founded theories from the literature.

2.1 Framework

I introduce the model of this section. There are three investors who choose how much to buy of a single asset in fixed supply S.[8] The short-term investor ST and long-term investor LT decide their demand based on the short-term return signal P_t/P_{t-1} and past long-term return signal P_{t-1}/P_{t-s} of the asset. One period corresponds to one quarter, and s captures long horizons of one year. Investor ϕ has noisy demand, which is persistent.

The three investors play distinct roles in the model. The function of the investor with noisy demand, ϕ, is to generate persistent demand shocks. While I do not explicitly model the source of this persistence, underreaction to information shocks is an example of behavior

[8] In the quantitative model of section 3, I will re-introduce heterogeneity in the full cross-sections of stocks and investors.

that creates such a slow build-up of demand over time. The other two investors represent institutions such as mutual funds. They differ in the type of price signal they use and in the speed at which they enter positions. Outside the model, institutions exist on a spectrum ranging from high-frequency traders as fast investors trading on short-term signals on the one extreme and Warren Buffet's Berkshire Hathaway as an institutional value investor on the low-frequency end. The two investor types in the model are not placed on either extreme but live at frequencies of a quarter (ST) and a year (LT) to align with formation periods from momentum strategies (e.g., Jegadeesh and Titman, 1993).

I parametrize this intuition through demand functions for the three investor types. Specifically, I log-linearize demand $D(P_t/P_{t-1})$ in recent and long-term returns around zero:

$$d_t^{ST} = \underline{d}^{ST} - \mathcal{E}_{\text{recent}} \times (p_t - p_{t-1}) \tag{1}$$

$$d_t^{LT} = \underline{d}^{LT} - \mathcal{E}_{\text{long-term}} \times (p_{t-1} - p_{t-s}) \tag{2}$$

$$D_t^{\phi} = \phi \times D_{t-1}^{\phi} + \epsilon_t^{\phi}, \tag{3}$$

where lowercase letters denote log values, $p_t - p_{t-1}$ denotes the recent log return between times $t-1$ to t, and $p_{t-1} - p_{t-s}$ is the longer-term return.

The recent elasticity $\mathcal{E}_{\text{recent}}$ captures how aggressively the short-term investor ST trades against price changes over the most recent quarter; the higher $\mathcal{E}_{\text{recent}}$, the more elastic the demand of the short-term investor to variation in the price p_t relative to a recent reference level, p_{t-1}. That is, if prices decrease by 1% relative to the previous period, the short-term investor will increase her demand by $\mathcal{E}_{\text{recent}}$%. Beyond that, $\underline{d}^{ST}$ captures an average baseline demand for the short-term investor. This component reflects price-insensitive components of investor demand; for example, based on fundamentals or preferences for the asset capturing additional criteria (e.g., ESG scores).[9]

[9] The empirical framework in section 3 will go into more detail about modeling baseline demand.

In contrast, the long-term investor LT only scans prices at a lower frequency, meaning they only form demand based on prices one quarter ago. The elasticity $\mathcal{E}_{\text{long-term}}$ captures how contrarian the long-term investor is, or equivalently, how elastically she trades against longer-term variation at the frequency of a year. And again, $\underline{d}^{LT}$ captures baseline demand for the investor.

Finally, the demand of the investor indexed by ϕ includes demand shocks ϵ_t^{ϕ}, which represent information shocks that enter her demand over time based on the persistence parameter, also denoted ϕ. If $\phi < 1$, the investor initially overreacts to shocks, but subsequently, the shock partially reverts. For $\phi = 1$, demand is a random walk where shocks are permanent. Finally, if $\phi > 1$, a demand shock at time $t-1$ is exacerbated further at time t, leading to a build-up of demand over time. The persistence captures underreaction to information: As the investor receives a signal about fundamentals, she initially only partially adjusts her position but subsequently increasingly incorporates the information into her demand.

Market Clearing. In equilibrium, the demand of all three investors has to sum to the supply of the asset, as shown in the standard market-clearing equation (4):

$$S - D_t^{\phi} = D_t^{ST} + D_t^{LT}, \quad \forall t \tag{4}$$

Substituting demand functions (1), (2), and (3) into the market-clearing equation (4) and solving for equilibrium price changes Δp_t yields:

$$\Delta p_t = \frac{1}{\mathcal{E}_{\text{recent}}} \left(\underline{d}^{ST} - \log \left(S - D_t^{LT} - D_t^{\phi} \right) \right) \tag{5}$$

Equation (5) shows how following a demand shock from noisy demand investor ϕ, the short-term investor is the only marginal investor willing to absorb the shock. Consequently, the price reflects her demand elasticity. Appendix A provides additional details and shows all derivations underlying results of this section.

2.2 Momentum from persistent demand shocks

Next, I show how the framework from the previous section can generate momentum. I start by emphasizing build-ups of demand over time, representing underreaction. To illustrate the mechanism in the simplest way possible, I focus on the model without differentiating between short- and long-term investors. This corresponds to a flat term structure of elasticities, i.e., $\mathcal{E}_{\text{recent}} = \mathcal{E}_{\text{long-term}} = \mathcal{E}$. Then, we can aggregate the two investors into one,

$$d_t = \underline{d} - \mathcal{E} \times (p_t - p_{t-s}), \tag{6}$$

with s again capturing longer horizons of one year. To generate momentum, consider demand shocks that increase in magnitude over time, $\phi > 1$.[10] When the investor indexed by ϕ receives positive new information, she partially incorporates this into her demand, ϵ_t^{ϕ}, and prices reflect the additional demand, but not enough to reflect the new information fully. For example, consider an initial demand shock to Apple at time $t = 1$ equal to 10% of supply S. There is a single contrarian investor with demand elasticity $\mathcal{E} = 1$ and who is endowed with 100% of supply at time 0. This is the example in Figure 1(a). Consequently, at $t = 1$, the 10% has to be provided by this single contrarian investor. From equation (5), the price impact of the shock is inversely proportional to the demand elasticity $\mathcal{E}$ times the size of the demand shock, which is about 10% at $t = 1$ for the example, as shown in Figure 1(b).

Over time, the investor increasingly incorporates news into prices; as the demand shock grows, prices increase further. This process represents underreaction to information similar

[10] I choose this parametrization for its simplicity in illustration. To retain stationarity, I could alternatively use more complex autocorrelation patterns that lead to a build-up of shocks over short horizons but reversal over longer horizons (e.g., Lochstoer and Muir, 2022). In my empirical framework, I relax such structural assumptions about the correlation structure of demand shocks and instead opt for a micro-identified approach.

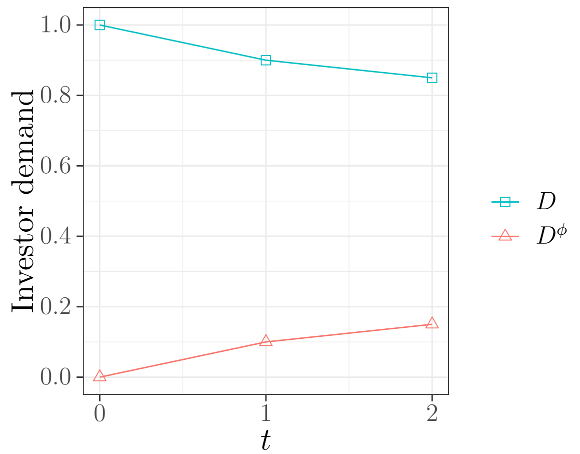
to Chan, Jegadeesh, and Lakonishok (1996). In broader economic terms, from the perspective of the contrarian investor, the build-up of demand represents repeated shifts of the residual supply curve. Section 2.5.1 discusses other mechanisms that generate persistent demand shocks, such as slow information diffusion of private information between many smaller investors (e.g., Hong and Stein, 1999) or delayed overreaction from belief dynamics with self-attribution bias (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998).

So what happens following at time t, following a demand shock ϵ_{t-1}^{ϕ} that moves equilibrium returns Δp_{t-1} at $t-1$? The equilibrium follow-on return is

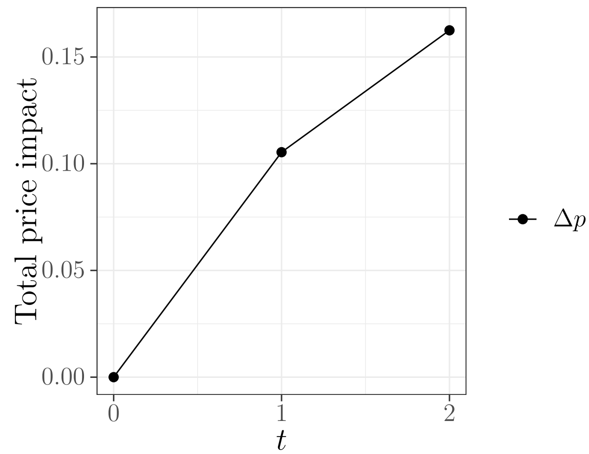
$$\Delta p_t = \left(\phi \frac{D_t}{D_{t-1}} - 1\right) \Delta p_{t-1} \approx (\phi - 1)\, \Delta p_{t-1}, \tag{7}$$

which is greater than Δp_{t-1} for $\phi > 1$ and sufficiently small demand shocks. Because the demand shock from time $t-1$ builds up further at t, there is additional price pressure, raising prices further: momentum. In the example of Figure 1, the persistence of demand shocks is parametrized through $\phi = 1.5$. That is, the shock grows from 10% to 15% of the supply of the asset at $t = 1$, with the follow-on price impact again being proportional to the inverse elasticity times $\mathcal{E}^{-1}$ times the size of the follow-on demand shock.

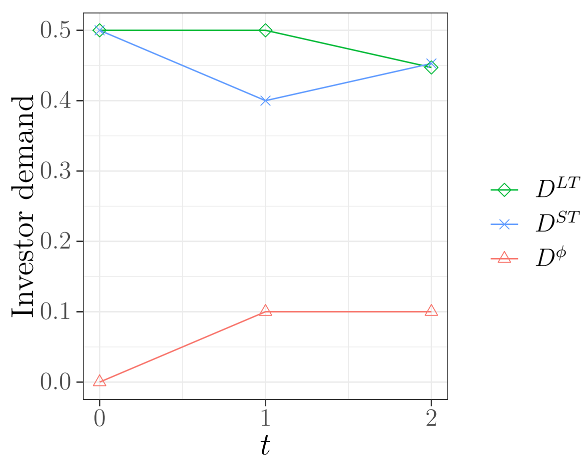
A critical feature of this model is that while the price-sensitive investor is contrarian in her trading against prices, she does not anticipate the dynamics of the noisy investor's demand shocks. The data bear this feature; there is evidence that predictable demand shocks move prices not (entirely) ahead of time but when the predictable demand shocks arrive in markets. For example, Hartzmark and Solomon (2022) show that dividend reinvestments create price pressure despite being predictable. Yet even in the presence of sophisticated arbitrageurs, theories of underreaction (e.g., Hong and Stein, 1999) can still play a role in equilibrium. This is especially the case if arbitrageurs' ability to correct mispricings is subject to limits-to-arbitrage (Shleifer and Vishny, 1997) or if it is difficult to distinguish between information and noise in prices.



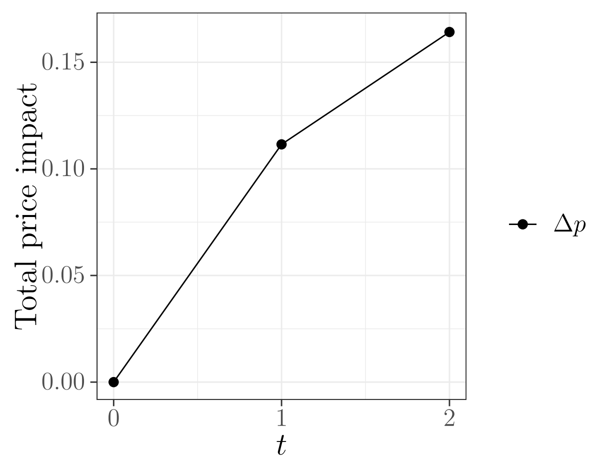
(a) Demand path (persistent demand shock)



(b) Price path (persistent demand shock)



(c) Demand path (elasticity term structure)



(d) Price path (elasticity term structure)

Figure 1. Evolution of demand and prices from persistent demand shocks and the term structure of demand elasticities.
The upper two panels of Figure 1 show the paths of investor demands on the left and price on the right in response to a persistent demand shock $\epsilon_1^{\phi} = 10\%$ of supply as of time $t = 1$. The shock builds up $\epsilon_2^{\phi} = 15\%$ at $t = 2$ ($\phi = 1.5$). At $t = 0$, the single contrarian investor is endowed with 100% of supply, $D_0 = 100\%$. The demand elasticity of the contrarian investor is $\mathcal{E}_{\text{recent}} = \mathcal{E}_{\text{long-term}} = 1$.
The lower two panels exemplify the evolution of investor demands and prices resulting from a downward-sloping term structure of demand elasticities following a constant shock over time, $\epsilon_1^{\phi} = \epsilon_2^{\phi} = 10\%$ ($\phi = 1.0$). The recent and long-term demand elasticities of the short-term and long-term investors are $\mathcal{E}_{\text{recent}} = 2$ and $\mathcal{E}_{\text{long-term}} = 1$, respectively, with both investors endowed with $D_0^{ST} = D^{LT} = 50\%$ of supply at $t = 0$.

2.3 Momentum from the term structure of demand elasticities

Above I have shown how time-series patterns in demand shocks build up to form momentum. Next, I propose an alternative mechanism, the term structure of demand elasticities, and show how it creates momentum from investors' differential responses to price signals across horizons. For expositional purposes, I fix the persistence of demand shocks at $\phi = 1$, a random walk with permanent demand shocks for demand D^{ϕ}.

Short-term price impact. Consider an initial equilibrium perturbed by the noise trader shock, ϵ_t^{ϕ}. How much does the demand shock move the equilibrium return Δp_t? To see this, first, define the residual supply $\tilde{S}$:

$$\tilde{S}_t \equiv S - D_t^{LT} - D_t^{\phi} \tag{8}$$

$\tilde{S}$ captures the residual supply after accounting for price-insensitive demand and represents the total demand the short-run investor has to absorb. We can now express the price impact of the demand shock as a function of residual supply. For example, consider again a 10% shock to the supply of Apple because a large Apple investor is exogenously forced to fire-sale her shares. What happens to the price of Apple? The answer depends on how willing the short-term contrarian investor is to absorb the shock. In contrast, the willingness of the long-run contrarian investor to absorb shocks does not matter for the short-term price impact because the long-term investor only responds to prices with a delay. In the presence of a hyper-elastic ($\mathcal{E}_{\text{recent}} = \infty$) short-run arbitrageur, who responds infinitely strongly to any tiny mispricing, Apple's price will remain anchored at its efficient level. In contrast, with inelastic demand, for example, $\mathcal{E}_{\text{recent}} = 2$ and the short-run investor owning 50% of Apple, the size of the demand shock is $10\% \div 0.5 = 20\%$ of the short-term investor's holdings. Therefore, her response is $20\% \times 0.5 = 10\%$ when prices decrease by 10%, fully offsetting the size of the shock. As a result, in equilibrium, the price of Apple stock declines by 10%. This is depicted in the lower panels of Figure 1. With fewer or less elastic short-run investors, the shock is only fully absorbed when the price response grows in magnitude. More formally, define aggregate elasticities as:

$$\bar{\mathcal{E}}_{\text{recent},t} \equiv D_t^{ST} \mathcal{E}_{\text{recent}} \tag{9}$$

$$\bar{\mathcal{E}}_{\text{long-term},t} \equiv D_t^{LT} \mathcal{E}_{\text{long-term}} \tag{10}$$

Then, equilibrium condition (5) can be re-written as:

$$\Delta p_t = -\bar{\mathcal{E}}_{\text{recent},t}^{-1} \Delta \tilde{S}_t. \tag{11}$$

The price impact of a shock to the residual supply is proportional to the inverse of the aggregate recent elasticity $\bar{\mathcal{E}}_{\text{recent},t}$.[11] The more elastic the short-run investor, the steeper the demand curve she is moving along, and the more willing she becomes to absorb the demand shock at small price discounts. Thus, the less the price changes in the perturbed relative to the initial equilibrium.

Long-term price impact. Now move forward one quarter. What is the impact of a demand shock ϵ_{t-1}^{ϕ} on the equilibrium price change Δp_t? Again, assume that the size of the demand shock is constant between $t-1$ and t, i.e., $\phi = 1$. From equilibrium condition (5):

$$\Delta p_t = -\frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}} \Delta p_{t-1} \approx -\underbrace{\frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}}{\bar{\mathcal{E}}_{\text{recent},t}}}_{\substack{\text{term structure of} \\ \text{demand elasticities}}} \Delta p_{t-1} \tag{12}$$

[11] Equivalently, Gabaix and Koijen (2020) show that the price impact of aggregate flows is the inverse of their macro elasticity.

Δp_{t-1} denotes the original price impact of the demand shock ϵ^{ϕ}_{t-1} at time $t-1$. The follow-on price impact of a past shock, Δp_t, is controlled by the term structure of demand elasticities:[12] When $\bar{\mathcal{E}}_{\text{long-term},t} = \bar{\mathcal{E}}_{\text{recent},t}$, the term structure of elasticities is flat. Due to the different investment horizons, the short-term investor passes the asset on to the long-term investor. Still, since they are equally elastic in their aggregate responses, meaning they are equally willing to absorb shocks, they do so at the same price the short-term investor purchased the asset for. Consequently, the past demand shock has no additional impact on current prices beyond the last period's initial price impact, and $\Delta p_t = 0$. When $\bar{\mathcal{E}}_{\text{long-term},t} > \bar{\mathcal{E}}_{\text{recent},t}$, long-term investors are more elastic than short-term investors. In this case, the long-term investors are willing to provide the liquidity needed to continue to absorb the $t = 1$ shock at a cheaper price, and therefore the initial price impact partially reverses. In contrast, when $\bar{\mathcal{E}}_{\text{long-term},t} < \bar{\mathcal{E}}_{\text{recent},t}$, the term structure of elasticities is downward-sloping. When the short-term investors close their positions at $t = 2$, the long-term investors are unwilling to take on the liquidity provision unless the initial price impact is further exacerbated. This is what I find to be the case in the data. Investors are less responsive to longer-term price variation, so the initial price changes must be amplified to maintain equilibrium, generating momentum.

2.4 Aggregation

In reality, the distinction between short-term and long-term contrarian investors is less clear-cut than described so far; investors live on a spectrum regarding how aggressively they trade against recent versus longer-term price changes. For example, fast short-term traders with high elasticity to recent price changes may not close their positions fully within a year of a shock, but instead do so gradually over time. To capture this, I leave behind the strict dichotomy of short- and long-term investors. Instead, I introduce a decentralized version of

[12] The term structure of demand elasticities is conceptually distinct from other term structures in the finance literature (e.g., interest rates, risk premia, or cash flows); it is backward-looking in that it refers to how investors' demand is shaped differently by different past price changes, rather than how they respond to expected future prices.

the model. It contains many investors, indexed by i, whose behavior is defined through their recent elasticity $\mathcal{E}_{\text{recent},i}$, longer-term elasticity $\mathcal{E}_{\text{long-term},i}$, and baseline demand $\underline{d}_i$:

$$d_{it} = \underline{d}_i - \mathcal{E}_{\text{recent},i} \times (p_t - p_{t-1}) - \mathcal{E}_{\text{long-term},i} \times (p_{t-1} - p_{t-s}) \tag{13}$$

Similar to the dichotomized version of the previous section, the relation between an investor's recent and long-term elasticity defines whether an investor uses short-term or long-term price signals and how fast they are in incorporating them into their demand.

Demand shocks are still the result of a separate investor with noisy demand for this section, as described in equation (3).[13] This model aggregates well; the aggregate elasticity on the stock level is equal to the demand-weighted average of elasticities across investors, similar to equations (9) and (10):

$$\bar{\mathcal{E}}_{\text{recent},t} \equiv \sum_i D_{it}\ \mathcal{E}_{\text{recent},i} \tag{14}$$

$$\bar{\mathcal{E}}_{\text{long-term},t} \equiv \sum_i D_{it}\ \mathcal{E}_{\text{long-term},i} \tag{15}$$

This enhanced model combines both channels into one equation,[14]

[13]Alternatively, I could decentralize the demand shocks to institutions as well. I do so in the empirical framework, where I also allow for arbitrary time-series patterns of demand shocks, which can differ across institutions. Therefore, my empirical model does not require a single parameter ϕ that can summarize the behavior of demand shocks but instead is flexible enough to entertain complex patterns.

[14]Equation (17) corresponds to an approximation of the follow-on price change because compositional changes in ownership structure lead to time-series variation of aggregate elasticities. Equation (16),

$$\Delta p_t = \left((\phi - 1)\ \frac{\bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}} - \frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}} \right) \Delta p_{t-1}, \tag{16}$$

exhibits the precise formulation for the follow-on price changes, incorporating a wedge between the aggregate recent elasticities as of $t-1$ and t. However, such composition-driven time-series changes are small from period to period, motivating the approximation in equation (17), which treats aggregate elasticities as locally constant.

$$\Delta p_t = \Big(\underbrace{\phi - 1}_{\substack{\text{persistent} \\ \text{demand shocks}}} - \underbrace{\frac{\bar{\mathcal{E}}_{\text{long-term}} - \bar{\mathcal{E}}_{\text{recent}}}{\bar{\mathcal{E}}_{\text{recent}}}}_{\substack{\text{term structure of} \\ \text{demand elasticities}}} \Big) \Delta p_{t-1}. \tag{17}$$

Equation (17) shows that the price change Δp_{t-1} from a demand shock at time $t-1$ is followed by a "momentum return" Δp_t proportional to Δp_{t-1}. When demand shocks are persistent, $\phi > 1$, a high (demand-shock-implied) return Δp_{t-1} is followed by an additional positive return Δp_t because the shock builds up further in size. This is the channel described in section 2.2. Similarly, when investors in aggregate get less responsive to the demand shock, $(\bar{\mathcal{E}}_{\text{long-term}} - \bar{\mathcal{E}}_{\text{recent}})/\bar{\mathcal{E}}_{\text{recent}} < 0$, then there again is an additional positive price change controlled by the magnitude of the downward slope of the term structure of demand elasticities.[15]

I collect these results about the making of momentum in Proposition 1:

Proposition 1. *For price-elastic investors with demand* (13)*, noisy demand investors* (3)*, and fixed supply S, the time t follow-on price impact of a $t-1$ demand shock that initially moved prices by Δp_{t-1} is*

$$\Delta p_t \approx \left(\phi - 1 - \frac{\bar{\mathcal{E}}_{\textit{long-term}} - \bar{\mathcal{E}}_{\textit{recent}}}{\bar{\mathcal{E}}_{\textit{recent}}} \right) \Delta p_{t-1}, \tag{18}$$

where the aggregate recent elasticity $\bar{\mathcal{E}}_{\textit{recent}}$ and longer-term elasticity $\bar{\mathcal{E}}_{\textit{long-term}}$ are defined in equations (14) *and* (15)*, respectively.*

Momentum arises from:

(a) Build-up of demand over time, $\phi > 1$.

(b) A term structure of demand elasticities that is downward-sloping, $(\bar{\mathcal{E}}_{\textit{long-term}} - \bar{\mathcal{E}}_{\textit{recent}})/\bar{\mathcal{E}}_{\textit{recent}} < 0$.

[15] Similarly, Atmaz et al. (2022) emphasize that the more contrarians rely on recent stock performance in forming their beliefs, the stronger the magnitude of time-series momentum.

The results from Proposition 1 follow directly from derivations in Appendix A. Proposition 1 shows that two distinct channels drive time-series patterns of price changes: the persistence of demand shocks and the aggregate term structure of demand elasticities. Momentum arises when there is a build-up in demand over time, $\phi > 1$, or when the term structure of demand elasticities is downward-sloping, $(\bar{\mathcal{E}}_{\text{long-term}} - \bar{\mathcal{E}}_{\text{recent}})/\bar{\mathcal{E}}_{\text{recent}} < 0$. In contrast, mean reversion in demand, $\phi < 1$, or an upward-sloping term structure of elasticities create reversals in stock returns. This paper's goal is to quantify the importance of these two channels for making momentum in equilibrium. To this end, I show how to incorporate these two channels into an asset demand system in section 3. My estimates suggest that a downward-sloping term structure of demand elasticities is the primary driver of momentum returns between 1999 and 2020.

2.5 Foundations of momentum

The framework above shows how stock momentum arises from different meta-theories regarding investors' dynamic trading. It distinguishes investors' dynamic response to prices and aggregate underreaction from persistent investor demand shocks. As I show below, many economic channels, both rational and behavioral in nature, operate within these two broad categories.[16] In practice, all of these mechanisms play some role in making momentum. By remaining agnostic about specific foundations, my empirical framework can separate the net importance of what lies at the core of creating momentum: demand shocks vis-à-vis differential responses to price changes across horizons.

First, I outline some theories of why investors would trade in a way that generates momentum through persistent demand shocks: underreaction to information, slow information diffusion, liquidity, and self-attribution bias. Second, I highlight theories that shape the term structure of demand elasticities: the evolution of arbitrage intensities across horizons,

[16] Many explanations for momentum are based on behavioral mechanisms. Nevertheless, there exist examples of rational mechanisms both for the slow build-up of demand and the downward-sloping terms structure of elasticities. As such, my classification is distinct from categorizing theories into rational and behavioral.

learning from prices, and the disposition effect.

2.5.1 Persistent demand shocks

Underreaction to information. Persistent demand shocks are the first mechanism through which my model can generate momentum. Some models create persistent demand shocks through underreaction to information, as in Chan, Jegadeesh, and Lakonishok (1996). Investors initially only partially react to earnings surprises.[17][18] Over time, however, they increasingly incorporate the news into their demand, leading to a drift in prices. In the data, this gradual adjustment leads to a slow build-up in demand, as modeled in section 2.2, with $\phi > 1$.

Slow information diffusion. A similar example is slow information diffusion by newswatchers in Hong and Stein (1999). When some but not all investors receive private signals, then the initial total response to fundamental news is weak, underreaction. This aggregate underreaction is more pronounced if early informed investors cannot strategically front-run the demand from investors who receive the signal later. Then, as information slowly spreads, more investors respond, generating price drifts: momentum. Aggregated into one investor, this is the same mechanism as for underreaction to information. However, these channels differ in whether underreaction occurs within one investor or spread across many.[19]

Self-attribution bias. Biased confidence dynamics, as in Daniel, Hirshleifer, and Subrahmanyam (1998) or Luo, Subrahmanyam, and Titman (2020) can also create time-series

[17] While underreaction to information is often regarded as behavioral, slow updating to new information can also be the result of Bayesian learning about fundamentals (e.g., Ghaderi, Kilic, and Seo, 2022).

[18] Similarly, in Barberis, Shleifer, and Vishny (1998), investors underreact to earnings shocks when mistakenly believing the shocks to be mean-reverting, leading to momentum. In contrast, when investors overreact to shocks, for example, because of extrapolation (e.g., De La O and Myers, 2021; Bordalo et al., 2022), then $\phi < 1$, and returns exhibit reversals. To create momentum alongside reversal, investors' initial response to earnings announcements has to be slow, leading to underreaction followed by delayed overreaction.

[19] Hirshleifer (2020) emphasizes more generally that momentum can result from biases in the social transmission process rather than from individual-level biases. For example, Barardehi, Bogousslavsky, and Muravyev (2023) provide evidence that momentum and short-term reversal result from investor underreaction to other investors' informed trades.

patterns in returns that resemble momentum. Investors get asymmetrically more confident when their views are validated. In particular, an investor who initially receives a positive private signal and invests will subsequently, following a positive public news release, overreact and invest too much. This overreaction stems from self-attribution bias: Investors update their positions more aggressively if observed signals align with their prior beliefs.[20] This example of delayed overreaction leads to momentum because, more often than not, a change in demand is followed by another demand change in the same direction: persistet demand shocks.

2.5.2 Term structure of demand elasticities

Arbitrage across horizons. Non-flat term structures of demand elasticities can arise from segmentation in arbitrage activity across different horizons. Section 2.3 outlined a model in this spirit. When two sets of arbitrageurs operate at different frequencies and differ in their aggregate willingness to absorb shocks, then prices will generally vary as the asset changes hands from being owned by the shorter-horizon to the longer-horizon arbitrageur. In particular, if short-horizon arbitrageurs are relatively more willing to absorb shocks, then the term structure of demand elasticities is downward-sloping. Specifically, long-term arbitrageurs might be less inclined to absorb shocks because of limits to arbitrage (e.g., Shleifer and Vishny, 1997): They might have to take on more long-run fundamental risk or might be subject to funding frictions resulting from a misalignment between the investment horizon of their assets compared to the maturity structure of their liabilities.

Learning from prices. The model of Hong and Stein (1999) features momentum traders alongside newswatchers. Momentum traders are investors who use past returns as a signal

[20]The dynamics of confidence can alternatively be interpreted as creating momentum from time-series variation of demand elasticities. However, this conceptually differs from how the term structure of demand elasticity creates momentum from investors differentially loading on past price changes at different horizons in forming their portfolios.

for future expected returns,[21] which is informative due to the slow information diffusion of newswatchers' private information. In the model, momentum traders cannot post demand curves conditional on prices in the style of Grossman and Stiglitz (1980) and, therefore, only learn from past prices. Thus, the behavior of momentum traders is inelastic at short horizons, $\mathcal{E}_{\text{recent}} = 0$, and, due to the learning channel, exhibits negative elasticity to longer-term variation in prices, $\mathcal{E}_{\text{long-term}} < 0$. This combination of zero recent elasticity and negative longer-term elasticity generates a downward-sloping term structure of elasticities (i.e., $\mathcal{E}_{\text{recent}} > \mathcal{E}_{\text{long-term}}$) and hence, momentum in stock returns.[22][23] More generally, learning from prices leads to more inelastic demand (Haddad, Huebner, and Loualiche, 2022), especially for uninformed investors who cannot distinguish between information and noise in prices (Davis, Kargar, and Li, 2022).[24][25] To the extent that learning from prices is instantaneous and long-lasting, it shifts elasticities at all horizons up or down but does not create differential behavior in relative terms. However, there are many examples of deviations from these assumptions. First, Davis (2022) argues that across many canonical portfolio choice models (e.g., Brandt, Santa-Clara, and Valkanov, 2009), investors learn about expected returns from past returns but do not post demand curves that enable learning from current equilibrium prices (e.g., Grossman and Stiglitz, 1980; Veldkamp, 2011). Second, past returns can enter belief formation through weights that are not constant across time. Richer term structures of elasticities represented through more than two elasticities could model such patterns in belief-formation weights. Non-constant weights in belief formation can occur rationally when investors learn about moving targets (e.g., Collin-Dufresne, Johannes, and Lochstoer, 2016). Alternatively, it can reflect a wedge between subjective and objective expectation formation,

[21] A conceptually related yet less rigorous version of learning from past prices is outright positive-feedback "trend-chasing" behavior, as in Long et al. (1990).

[22] More precisely, momentum traders exacerbate the price drift caused by slow information diffusion. Relatedly, Hong, Lim, and Stein (2000) show that momentum strategies work better for stocks with slow information diffusion, as proxied by less analyst coverage and smaller firm size.

[23] Lou and Polk (2021) show that the larger the momentum crowd, that is, the more momentum traders there are, the more prices overshoot fundamentals and revert subsequently.

[24] See Adam and Nagel (2022) for a review of the role of expectation formation in asset pricing.

[25] Consistent with this idea, the pass-through from exogenous variation in prices to investors' expected returns (Charles, Frydman, and Kilic, 2022; Chaudhry, 2022) and portfolios (Giglio et al., 2021) is weak.

for example, when investors' lived experiences decay slowly (Malmendier and Nagel, 2011, 2016; Egan, MacKay, and Yang, 2022; Nagel and Xu, 2022) or as the consequence of investors extrapolating past returns (Barberis and Shleifer, 2003; Greenwood and Shleifer, 2014; Barberis et al., 2015, 2018; Cassella and Gulen, 2018).[26] Notice how in contrast to earnings extrapolation, which works through the autocorrelation patterns of demand shocks, return extrapolation affects the term structure of demand elasticities.[27]

Disposition effect. As a final example, Grinblatt and Han (2005) show that the disposition effect, investors tendency to sell winners too early and losers too late, can generate momentum in stock prices. Consider a setting in which investors' demand has a rational component based on deviations of equilibrium prices from fundamental values but also features deviations of equilibrium prices from some perceived reference prices, their cost bases. This corresponds to a demand function with two elasticities. As long as the reference price corresponds to past stock prices, it is equivalent to two elasticities for different time horizons. To align the time horizons with momentum frequencies, consider the stock price from one quarter ago as the reference price. Then investors overreact to recent price changes; that is, they are more elastic to variation in prices over the most recent quarter, $\mathcal{E}_{\text{recent}} > \mathcal{E}_{\text{long-term}}$, which corresponds to a downward-sloping term structure of elasticities and generates momentum.

3 Estimating Dynamic Trading

In this section, I estimate the two channels that create momentum in equilibrium: the evolution of demand shocks and the term structure of demand elasticities. I start by proposing

[26]As emphasized by Da, Huang, and Jin (2021), extrapolation models generate reversals because the impact of past shocks decays over time. However, such models differ in terms of their ability to generate momentum based on whether investors' response to past returns is hump-shaped across horizons. This occurs when investors do not immediately incorporate returns into belief formation.

[27]My framework can be used to contrast the distinct roles of extrapolation based on fundamentals and prices. In a related paper, McCarthy and Hillenbrand (2021) entertain the possibility of both return- and cash flow extrapolation and time-varying risk aversion as potential drivers for stock market fluctuations. In their estimates, they ascribe approximately equal roles to each of them.

a demand system in the style of Koijen and Yogo (2019) that accounts for equilibrium and incorporates both persistent demand shocks and the term structure of demand elasticities. Then, I introduce a novel identification strategy for demand estimation in the presence of dynamic trading, allowing me to separate both mechanisms empirically. Finally, I estimate the model for all institutional investors in the U.S. stock market between 1999 and 2020.

3.1 Quantitative model

Investor demand. Unlike in the model from section 2, investors choose portfolios of stocks. Koijen and Yogo (2019) show that a logit of portfolio weights is a good way of modeling portfolio choice, as it ensures that portfolio weights for each investor sum to 1 and allows for substitution across assets.[28] I follow this approach. In particular, I use a log-linear specification to model portfolio weights relative to an outside asset 0, $\log\left(w_{it}(n)/w_{it}(0)\right)$, where $w_{it}(n)$ indexes the investor i's portfolio weight in stock n at time t. The resulting portfolio demand is

$$\underbrace{\log \frac{w_{it}(n)}{w_{it}(0)}}_{\text{demand}} = \underbrace{(1-\mathcal{E}_{\text{recent},i})\ \Delta p_t(n)}_{\text{recent elasticity}} + \underbrace{(1-\mathcal{E}_{\text{long-term},i})\ \left(\sum_{s=1}^{3} \Delta p_{t-s}(n)\right)}_{\text{long-term elasticity}} + \underbrace{\underline{d}_{0it} + \underline{d}'_{1i} X_t(n)}_{\text{characteristics}} + \underbrace{\epsilon_{it}(n)}_{\text{latent}}. \tag{19}$$

This specification for investor demand parametrizes both mechanisms for creating momentum: the term structure of demand elasticities capturing different intensities of arbitrage across horizons and persistent demand shocks representing underreaction. In particular, the demand system's first two terms capture arbitrage intensities through price-elastic demand components. When the price of an asset rises, investors' demand for it decreases. The larger the elasticity, the more aggressively the investor trades against variation in prices; that is,

[28] The logit specification implies substitution that is proportional to portfolio weights. Koijen and Yogo (2020) use a nested-logit model that generates more flexible substitution patterns across countries and asset classes but which is difficult to operationalize within the US stock market.

the higher the level of arbitrage intensity, loosely defined. But from section 2, what matters for momentum is not so much the level of arbitrage but the relative differences in arbitrage intensities across horizons. So as before, I operationalize this intuition by allowing investors to respond differentially to recent and longer-term variation in prices: two separate parameters, $\mathcal{E}_{\text{recent},i}$ and $\mathcal{E}_{\text{long-term},i}$. This parametrization is an innovation relative to the existing literature, which treats demand elasticities as constant for any variation contained in today's prices.[29] It captures momentum from differences in arbitrage intensities; When an investor has $\mathcal{E}_{\text{recent},i} > \mathcal{E}_{\text{long-term},i}$, the investor has a downward-sloping term structure of elasticities, contributing to momentum.

To align my elasticity estimates with the time horizons in the momentum literature (Jegadeesh and Titman, 1993), I separate the price change over the last year into the most recent quarter and the three preceding quarters. That is, I model the demand as of December 31 as a log-linear function of the price change between October and December 31 (the price-elastic demand to recent price changes) and the price change between December 31 of the previous year and October 31 (the price-elastic demand to longer-term price changes). This approach is flexible enough to capture momentum from the term structure of demand elasticities while at the same time aggregating well in equilibrium. In the estimation, I impose downward-sloping demand curves for the elasticity to recent price changes, $\mathcal{E}_{\text{recent},i} \geq 0$, which is sufficient for the existence of counterfactual prices in the decomposition exercise in section 4 (Koijen and Yogo, 2019). However, I allow negative longer-term elasticities to capture learning from past prices or trend-chasing more generally, as is the case for momentum traders in Hong and Stein (1999).[30]

[29] My model does not, strictly speaking, nest the constant elasticity model of Koijen and Yogo (2019) because I do not allow for flexible long-term elasticities beyond the horizon of one year. Instead, I assume that long-term elasticities beyond a year are 1 across investors. In an alternative specification, I consider subtracting prices from the left-hand side of equation (19) and omit the ones as parts of the recent- and longer-term elasticity terms. This corresponds to setting investors' unmodeled long-term elasticities to zero. However, it generates strong momentum at long horizons, counterfactual to long-term overreaction and reversal (e.g., De Bondt and Thaler, 1985). Therefore, I use a long-term target elasticity of 1, slightly higher than the average elasticities estimated in Koijen and Yogo (2019).

[30] One might be concerned that the downward-sloping term structure of elasticities estimates might result from allowing negative elasticities to long-term but not recent price changes rather than identifying investors'

The last two components constitute the baseline level of demand and combine both investors' demand for stock characteristics and unobserved, latent demand. The evolution of baseline demand creates momentum from a slow build-up over time, capturing underreaction. More precisely, the third component of the demand function is $\underline{d}_{0it} + \underline{d}'_{1i} X_t(n)$ and reflects investor-specific functions of common stock characteristics. I include book equity, profitability, investment, and dividend yield. One interpretation of investors' demand loading on these characteristics is that they use firm fundamentals, as captured by these stock characteristics, to form their beliefs about expected returns. Finally, latent demand captures unobserved demand shocks. Such shocks may correspond to private information or, more generally, omitted stock characteristics. However, latent demand can also capture investor tastes for specific stocks or noise trading. Underreaction to either observed characteristics or private information induces a build-up of the baseline level of demand over time and, therefore, momentum.

Investor assets. While the assets-under-management process is less important for the estimation of investor portfolio demand, it does play a role in counterfactuals: If the return to an asset an institution holds had been different, the evolution of its asset dynamics would have changed as well. Therefore, I partially endogenize the asset dynamics of institutions. That is, I separate out the portions of asset dynamics that are endogenous through portfolio returns from a flow component, which I consider invariant to the equilibrium. This is unlike previous papers in the demand-system literature, which treat the evolution of an institution's assets under management as exogenous.

$$A_{it} = A_{it-1} \left(1 + f_{it} + w_{it-1}(n)' \Delta p_t(n)\right), \quad \forall i. \tag{20}$$

dynamic trading against prices. If that were the case, I should find steeply downward-sloping term structures of demand elasticities among the initially inelastic investors. However, this is counterfactual to the estimation results depicted in Figure 2 and, therefore, unlikely to pose an issue.

The assets under management A_{it} of institutions in equation (20) are functions of past assets A_{it-1}, flows f_{it} and equilibrium portfolio returns $w_{it-1}(n)'\Delta p_t(n)$.[31]

Equilibrium returns. Equilibrium returns are determined as market-clearing returns, solving the equilibrium of individual demands. Normalizing the number of shares to 1, the market-clearing equation for the log equilibrium return is

$$\Delta p_t(n) = p_t(n) - p_{t-1}(n) = \log\left(\frac{\sum_i A_{it} w_{it}(n)}{\sum_i A_{it-1} w_{it-1}(n)}\right), \quad \forall n, \tag{21}$$

where the portfolio weight $w_{it}(n)$, and thus the right-hand-side of equation (21), is decreasing in the return $\Delta p_t(n)$.[32] This guarantees the existence of equilibrium for the decomposition in section 4.1.[33]

Momentum from dynamic investor trading. As I demonstrated in section 2, the model can generate momentum from two dimensions of investor trading.[34] First, momentum is generated from investors with a downward-sloping term structure of elasticities. These are investors who react to prices in a more aggressively contrarian way at short horizons, but subsequently become less aggressive. In the data, I find strong support for this mechanism, which could reflect the dynamics of arbitrage, price-chasing behavior, or learning from past

[31]Unlike for mutual funds, exact flows and returns for institutions are not readily available in the data. I manually separate them by making an assumption about the timing of portfolio changes between quarter-end cutoff dates: I assume that institutions keep their quarter-end holdings until just before the next quarter-end. Under this assumption, I can separate out an institution's portfolio return $w'_{it-1}\Delta p_t(n)$ and reverse-engineer inflows as $f_{it} \equiv (A_{it} - A_{it-1})/A_{it-1} - w'_{it-1}\Delta p_t(n)$.

[32]Technically, there is also the wealth effect from equation (20). As I show in Appendix B.3, this effect can, in principle, generate negative elasticities for passive investors with concentrated portfolios. Practically, however, I do not find this to be of issue. In particular, in counterfactual exercises my numerical algorithm converges to an equilibrium within few iterations.

[33]For uniqueness of the equilibrium, there needs to be at least one non-passive investor with $\mathcal{E}_{\text{recent},i} > 0$ (Haddad, Huebner, and Loualiche, 2022) in the stock. The condition is satisfied for every stock at each time.

[34]Because the model of section 2 features a single asset, it does not distinguish cross-sectional and time-series momentum (e.g., Moskowitz, Ooi, and Pedersen, 2012). In contrast, the quantitative model is designed to represent portfolios of assets. Since investors' demand function in equation (19) is a function of price changes, rather than price change relative to the aggregate market, it corresponds to a model of time-series momentum.

prices.

Second, there is the evolution of demand shocks, $\epsilon_{it}(n)$. This is the component of the demand system that captures many theories of underreaction. For example, when an investor receives a private signal, she will incorporate it into her latent demand. But if initially, she does not fully incorporate the information into her demand, then there will be persistence in her demand shocks, which is underreaction. Latent demand will capture both the dynamics of underreaction within the same investor across time and underreaction "in aggregate", which occurs when a demand shock of some investor predicts future shocks of others. That is, underreaction can occur within the same investor, but it can also occur when some investor has early access to information, and information diffusion is slow (Hong and Stein, 1999). Either way, it generates persistence in aggregate latent demand.

3.2 Data

I follow Koijen and Yogo (2019) and Haddad, Huebner, and Loualiche (2022) in obtaining stock-level data and data on portfolio holdings for the U.S. stock market. Data on stock prices, returns, dividends, and shares outstanding are from CRSP, and book equity, profitability, and investment are from COMPUSTAT.

In addition, I source data on institutional investors' portfolio holdings between Q4 1999 and Q4 2020 from regulatory 13F filings available on the SEC EDGAR website using the method of Backus, Conlon, and Sinkinson (2019, 2020). Institutions with at least \$100mn in assets under management are required to file quarterly reports of their entire stock positions to the SEC, which sums to a total coverage of about 80% of total U.S. stock market capitalization. I group the remainder in an investor that I label the household sector.[35]

Finally, I obtain mutual fund data from the CRSP Survivor-Bias-Free US Mutual Fund Database. It contains information on mutual fund flows, returns, and holdings,[36] all used to

[35] I use the term "household sector" in a slight abuse of language, as it captures direct household holdings alongside, for example, holdings by small institutions below the reporting threshold and aggregate short interest (e.g., Mainardi, 2023).

[36] Like Dou, Kogan, and Wu (2020), I use the CRSP mutual fund holdings data as of Q3 2008, but the

construct the instrument for returns: mutual funds' flow-induced trading (Lou, 2012).

3.3 Identification

3.3.1 Identification problems and solutions

By substituting portfolio demand (equation (19)) into market-clearing (equation (21)), one can immediately see that latent demand affects equilibrium returns: positive demand shocks put upwards-price pressure on prices. Moreover, demand shocks may be correlated across investors. Both lead to mechanical correlation between returns and latent demand, i.e. $cov\left(\epsilon_{it}(n), \Delta p_t(n)\right) \neq 0$, and therefore introduce a bias in estimating the real-time elasticity $\mathcal{E}_{\text{recent},i}$, which is the investor's response to the return $\Delta p_t(n)$, via OLS. This is the standard simultaneity issue common to any setting of demand estimation. Below, I introduce an instrument that allows me to disentangle an investor's response to contemporaneous returns from their demand shocks.

But first, there is also a dynamic simultaneity issue specific to my setting. To see this, think of an investor with an underreaction type of demand shock. For example, at time $t-1$ a hedge fund receives a positive private signal and buys some shares of Apple. At time t, the fund buys even more.[37] In such a setting, it is difficult to disentangle other investors' dynamic responses to the shock from the dynamics of the shock itself. Investor demand correlates with longer-term price changes, but is that because of the response we want to identify — how investors react to long-term returns — or because of other investors reacting to the hedge fund's additional buying of Apple stock at time t? More formally, consider the moment condition under a valid instrument for returns, with $\widehat{\Delta p}_t(n)$ denoting instrumented returns:

Thomson Reuters Mutual Fund Holdings Data prior to that date.

[37]Slow trading by insiders can be optimal in models in which insiders try to conceal their private information (e.g., Kyle, 1985).

$$\mathbf{E}_i\left[\epsilon_{it}(n)|\mathbf{X}_t(n), \widehat{\Delta p}_t(n), \sum_{s=1}^{3}\Delta p_{t-s}(n)\right] = 0, \quad \forall i \tag{22}$$

This moment condition requires that latent demand $\epsilon_{it}(n)$ would have to be uncorrelated with the past returns $\Delta p_{t-1}, \Delta p_{t-2}$, and Δp_{t-3}. However, past returns are themselves equilibrium objects and have to satisfy the market clearing equations at time $t-1$, $t-2$, and $t-3$, respectively. By the exact same argument as for the standard simultaneity issue, $cov\left(\epsilon_{it-1}(n), \Delta p_{t-1}(n)\right) \neq 0$. This implies that the only way that $\epsilon_{it}(n)$ can be orthogonal to $\Delta p_{t-1}(n)$ is if latent demand itself is uncorrelated across time, i.e. $cov(\epsilon_{it}(n), \epsilon_{jt}(n)) = 0, \forall j$. However, the assumption of uncorrelated demand shocks across time is rejected both by the data and conceptually, as it rules out any momentum- or reversal generating persistence of demand shocks.

The dynamic simultaneity issue reflects a combination of persistent demand shocks and classic simultaneity issues. In order to solve it and identify investors' response to longer-term variation in returns, $\mathcal{E}_{\text{long-term},i}$, I proceed in a way that is analogous to solving the classic simultaneity problem: I isolate exogenous variation in longer-term price changes through an instrument orthogonal to $\epsilon_{it}(n)$. Assuming a valid instrument for longer-term returns, the moment condition then weakens to

$$\mathbf{E}_i\left[\epsilon_{it}(n)|\mathbf{X}_t(n), \widehat{\Delta p}_t(n), \sum_{s=1}^{3}\widehat{\Delta p}_{t-s}(n)\right] = 0, \quad \forall i. \tag{23}$$

Using another instrument for longer-term past price changes is not the only way of breaking apart the correlation between today's unobserved latent demand and past price changes; Adding a structural model that explicitly entertains the persistence of demand shocks through a parameter like in Section 2, or controlling for past holdings, might also be viable identification strategies. However, demand shocks are likely correlated across investors. For example, in Hong and Stein (1999), momentum is created from a build-up of demand across investors. Entertaining interactions between investors comes at the cost of complexity, making it impossible to estimate the demand of each investor in isolation (Haddad, Huebner, and Loualiche, 2022). In contrast, using an additional instrument for past price changes enables separately estimating demand curves investor-by-investor in a simple and computationally inexpensive way.

Yet there is another distinct advantage of using an instrument to identify investors' demand elasticity to longer-term price changes, particularly in using the same type of instrument as for recent price changes. There is much variation across estimates for micro-elasticities in the literature (e.g., Gabaix and Koijen, 2020). A potential reason is that different studies use different sources of variation for identifying demand elasticities and that investors respond differentially to price changes depending on the nature of the underlying shock. For example, an investor would want to and might be able to react differently to a shock to demand that represents noise than to one that represents information. By using the same type of variation for investors' responses to recent and longer-term price changes, I can ensure that my identification strategy can identify a term structure of demand elasticities, that is, an investor's differential responses across time to a specific type of shock, rather than variation from investors behaving differently in response to different types of demand shocks.

This argument seemingly threatens external validity; The term structure of demand elasticities might differ based on the type of shock used for identification. But conceptually, an investor's term structure of demand elasticities is about the relative difference of how investors respond to recent versus longer-term price changes, not the level of demand elasticity, and many economic channels that would affect the level of elasticity would do so the same way across horizons. In contrast, if the downward-sloping term structure of demand elasticities is driven by frictions set at the financial institution's level, it is likely easier to identify an externally valid term structure of demand elasticities compared to the level of demand elasticities. In line with this argument, in Section 4.2, I provide empirical evidence that the term structure of elasticities I identify holds up in the average data.

3.3.2 Instruments for recent and long-term returns

I proceed by introducing instruments for recent and longer-term returns. My instrument for recent returns is based on mutual fund flow-induced trading from Lou (2012).[38] The idea of this instrument is that when mutual funds face redemptions, they are forced to partially liquidate their holdings. Assuming that funds sell proportionally to their past holdings, a mutual fund's flows will generate cross-sectional variation in price pressure proportional to the fund's holdings. The instrument then aggregates this flow-induced price pressure across funds on the stock level.

$$FIT_t(n) \equiv \sum_j \frac{A_{jt-1} w_{jt-1}(n)}{P_{t-1}(n)} f_{jt} = \sum_j o_{jt-1}(n) f_{jt} \tag{24}$$

Equation (24) shows the definition of flow-induced trading more formally. Subscript j captures mutual funds, which is in contrast to before when variables were defined on the institution level more broadly. $P_{t-1}(n)$ captures the $t-1$ market capitalization of stock n, f_{jt} are the net inflows fund j received between $t-1$ and t, and o_{jt-1} captures the share fund j holds of stock n at time $t-1$.

Appendix section B.2 derives equation (24) by starting at the market clearing equation for returns (21), and making three adjustments to avoid sources of endogeneity: (i) replacing endogenous assets A_{jt} by $A_{jt-1}(1+f_{jt})$, (ii) replacing current portfolio weights $w_{jt}(n)$ by past weights $w_{jt-1}(n)$, and (iii) filtering from the set of all investors to mutual funds only. The latter is due to the availability of mutual-fund flow data, which is not the case for all financial institutions more generally. On the flip side, the variation that the instrument does use comes from mutual fund flows and past mutual-fund ownership: Stocks that last period

[38] Flow-induced trading can be viewed as a generalization of mutual fund fire sales-induced flows as in Coval and Stafford (2007).

were owned by mutual funds that subsequently received a lot of inflows have high flow-induced trading. Yet, in reality, mutual funds do not always allocate flows proportionally.[39] However, it is precisely the deviations from proportionality that are likely highly endogenous, so proportionality provides an exogenous selling rule for a Bartik-style instrument.

The instrument is a shift-share instrument, where the shifts are mutual fund flows, and the shares lagged portfolio shares. So the key identification assumption is that the shifts are ex-ante uncorrelated with the shares, or put differently, that mutual-fund flows are uncorrelated with mutual funds' past portfolio holdings. Yet, there is robust evidence that mutual fund flows follow past fund performance. For example, retail investors might use past fund returns to learn about fund manager skill.[40] Could the flow-performance relation potentially generate a violation of the identification assumption? Yes, because, by construction, lagged fund returns are a function of past fund holdings, inducing a correlation between a mutual fund's flows and its past portfolio holdings. To overcome the identification problem posed by the fund-performance relation, I orthogonalize mutual fund flows to past fund performance and past fund flows. That is, I regress quarterly mutual fund flows on the fund flows and fund performance of the four proceeding quarters and extract orthogonalized flows $\tilde{f}_{jt}$. The regression results are shown in Appendix Table IA.1.[41] Controlling for past fund performance and past flows allows me to isolate components of mutual fund flows that are plausibly exogenous to past holdings. I then construct orthogonalized flow-induced trading, $\widetilde{FIT}_t(n)$, analogously to before:

[39] For example, mutual funds could smooth in- and outflows through cash holdings, or not scale holdings up or down proportionally. Lou (2012) shows that, indeed, the pass-through of redemptions to proportional selling is close to 1 for 1, but somewhat lower for inflows, where only about 60 to 80 cents of each inflow dollar are used to scale up existing holdings.

[40] Early empirical evidence of the flow-fund relationship include Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998). Berk and Green (2004) is an example of a rational model that incorporate retail investors learning about mutual fund skill.

[41] I use specification 2 from Appendix Table IA.1, which introduces time-fixed effects to control for time-series variation in aggregate flows.

$$\widetilde{FIT}_{t-1\to t}(n) \equiv \sum_j o_{jt-1}(n)\tilde{f}_{jt} \tag{25}$$

In addition to the instrument for contemporaneous returns, I also require an instrument for longer-term returns, $\sum_{s=1}^{3} \Delta p_{t-s}(n)$. I proceed analogously to above, and define the instrument for longer-term returns as

$$\widetilde{FIT}_{t-4\to t-1}(n) \equiv \sum_j o_{jt-4}(n)\left(\tilde{f}_{jt-3} + \tilde{f}_{jt-2} + \tilde{f}_{jt-1}\right). \tag{26}$$

Relevance condition. Table 1 shows the results from first-stage regressions of recent and longer-term returns onto recent and longer-term flow-induced trading. In particular, columns 1 and 2 show first-stage results for current returns, while columns 3 and 4 focus on momentum-frequency returns. Columns 1 and 3 use raw FIT as proposed by Lou (2012). In contrast, columns 2 and 4 use my orthogonalized flow-induced trading measures, which constitute the basis for my empirical findings. All regressions include time-fixed effects and controls for profitability, investment, book equity, and dividend yield.

Across all regressions, the F statistic is above 10, and instruments are strongly statistically significant based on standard errors that are two-way clustered by date and stock. Coefficients on returns at the same horizon range between 1.4 to 2.3. A coefficient of 1 would be interpreted as a flow-induced inflow of 1% to a stock predicting a 1% return of the same stock.

I use the approach of Two-Sample Two-Stage Least Squares (Arellano and Meghir, 1992; Angrist and Krueger, 1992), meaning I estimate the first- and the second stage from different samples. This constitutes a deviation from Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2020), who estimate both within an investor's investment universe, defined as

Table 1. Relevance conditions for the recent and longer-term return instruments.

	Return $p_t - p_{t-1}$		Past Return $p_{t-1} - p_{t-4}$	
	(1)	(2)	(3)	(4)
$FIT_{t-1\to t}(n)$	1.399***		1.430***	
	(0.233)		(0.310)	
$FIT_{t-4\to t-1}(n)$	-0.354***		1.396***	
	(0.095)		(0.207)	
Orthogonalized $\widetilde{FIT}_{t\to t-1}(n)$		1.576***		0.338
		(0.285)		(0.396)
Orthogonalized $\widetilde{FIT}_{t-4\to t-1}(n)$		-0.280*		2.298***
		(0.130)		(0.197)
Date Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	257,941	257,941	257,941	257,941
R^2	0.216	0.216	0.137	0.136
F	22.000	24.169	49.638	56.982
F-test p value	0.000	0.000	0.000	0.000

Table 1 reports first-stage regressions of returns over the most recent quarter, $p_t - p_{t-1}$, and the three preceding quarters, $p_{t-1} - p_{t-4}$, onto flow-induced trading instruments between 1999 and 2020. Specifications (1) and (3) use flow-induced trading, as defined in equation (24), based on Lou (2012). Specifications (2) and (4) employ the enhanced instruments, as defined in equations and (25) and (26). That is, they are based on mutual-fund flows orthogonalized with respect to past fund flows and fund returns. All specifications use date-fixed effects and control for cross-sectionally de-meaned and standardized stock characteristics: log book equity, profitability, investment, and dividend yield. Standard errors are 2-way clustered by date and stock.

stocks the investor has held within the past three years.[42] However, investors might not only use stocks they held in the past in their formation of expected returns, which is connected to the first stage. Consequently, I relax this assumption and allow investors to learn from the entire cross-section of stocks, irrespective of which stocks they hold or are in their investment universe. Yet I do follow Koijen and Yogo (2019) in estimating the second stage within an investor's investment universe, as for many investors, the portfolio weights in most stocks are

[42]This approach has a potential identification issue coming from investors' investment universes being potentially larger than identified from past holdings, with investors endogenously not holding certain stocks. Under such a model, the stocks with low expected returns within the investment universe will be omitted from the formation of expected returns in the first stage.

zero.

My approach has an additional, more practical advantage. Exogenous yet relevant instruments for returns that are readily available for all stocks at all times are rare, especially for investors who hold relatively few stocks and have short time series of data available to begin with. Using the full panel of stocks and time in the first stage, I can satisfy relevance conditions without excluding or grouping investors with few observations.

Overidentifying restriction. My demand-system approach puts addtional restrictions on the coefficients in the first-stage regression that I use to assess the validity of my identification strategy. In particular, since recent orthogonalized flow-induced trading is, by construction, uncorrelated across time, the only way that it can be correlated with past price changes is if it is correlated with demand shocks, and demand shocks are persistent.[43] Intuitively, the economics of the instrument, price pressure, suggest a separation in terms of which instrument is relevant for which endogenous variable: past orthogonalized flows should only be relevant for past price changes. This can be summarized through the moment condition (27):

$$\mathbf{E}\left[\widetilde{FIT}_{t-1\to t}(n)\left(\sum_{s=1}^{3}\Delta p_{t-s}(n)\right)|\mathbf{X}_t(n),\mathbf{X}_{t-1}(n),\widetilde{FIT}_{t-4\to t-1}(n)\right]=0. \tag{27}$$

The additional moment condition is testable; It leads to the overidentifying restriction that the first-stage estimate of the coefficient on the recent orthogonalized flow-induced trading $\widetilde{FIT}_{t-1\to t}$ should be equal to zero. Based on the estimates in column 4, I do not reject the null hypothesis that this additional moment condition is satisfied.

This analysis points to an additional advantage of using the orthogonalized flow-induced trading instrument over its plain-vanilla counterpart: It allows me to assess the validity of the identification strategy by providing an overidentifying restriction. It is particularly well suited for evaluating the identification behind the term structure of demand elasticities.

[43] In the demand system, the evolution of characteristics can play a similar role. Then, controlling for characteristics isolates correlation with demand shocks.

This is because it validates the clean empirical separation between the slow build-up of demand and the term structure of demand elasticities for creating momentum by failing to reject that the shock used to isolate investors' response to past price changes coincides with persistent demand shocks. However, the same is not possible for the plain-vanilla version of flow-induced trading due to autocorrelation in the instrument. Similarly, there is no analogous overidentifying restriction on the coefficient of past orthogonalized flow-induced trading $\widetilde{FIT}_{t-1\to t}$ in the first-stage estimation of the recent return $p_t - p_{t-1}$ because a correlation between the return and the lagged instrument can arise for reasons that do not violate the exclusion restriction.[44]

3.4 Estimates

I estimate the model for each institution between 1999Q4 and 2020Q4 using a panel approach.[45] For each institution, I obtain one estimate for the recent elasticity $\mathcal{E}_{\text{recent},i}$ and longer-term elasticity $\mathcal{E}_{\text{long-term},i}$.

Figure 2 visualizes my estimates for recent and long-term elasticities through a scatterplot. Each point represents an institution with recent elasticity $\mathcal{E}_{\text{recent},i}$ on the x-axis and longer-term elasticity $\mathcal{E}_{\text{long-term},i}$ on the y-axis. The black dashed line has intercept zero and slope 1, meaning that any institution below the line has $\mathcal{E}_{\text{long-term},i} < \mathcal{E}_{\text{recent},i}$, a downward-sloping term structure of elasticities. The thick blue line is a fitted trend line based on a cubic regression.

As the smoothed blue line indicates, for institutions with recent elasticity $\mathcal{E}_{\text{recent},i}$ below 2.5, recent and longer-term elasticity are, on average, the same. Consequently, the term structure of elasticities is approximately flat for low-elasticity institutions. The types of

[44] While, by design, orthogonalized fund flows at t are uncorrelated with past fund flows, fund flows at t will be correlated with past orthogonalized fund flows. Therefore, the return $p_t - p_{t-1}$ could covary with the lagged instrument $\widetilde{FIT}_{t-1\to t}$ either because demand shocks correlate with the instrument — as before, a violation of the exclusion restriction — or because of autocorrelation of fund flows that affects both the recent price change and enters the instrument — not a violation of the exclusion restriction.

[45] I follow Koijen, Richmond, and Yogo (2020) and a robustness specification in Haddad, Huebner, and Loualiche (2022) in using a panel approach. In contrast, most other demand-system studies (e.g., Koijen and Yogo, 2019) estimate cross-sectionally and produce separate estimates at each point in time.

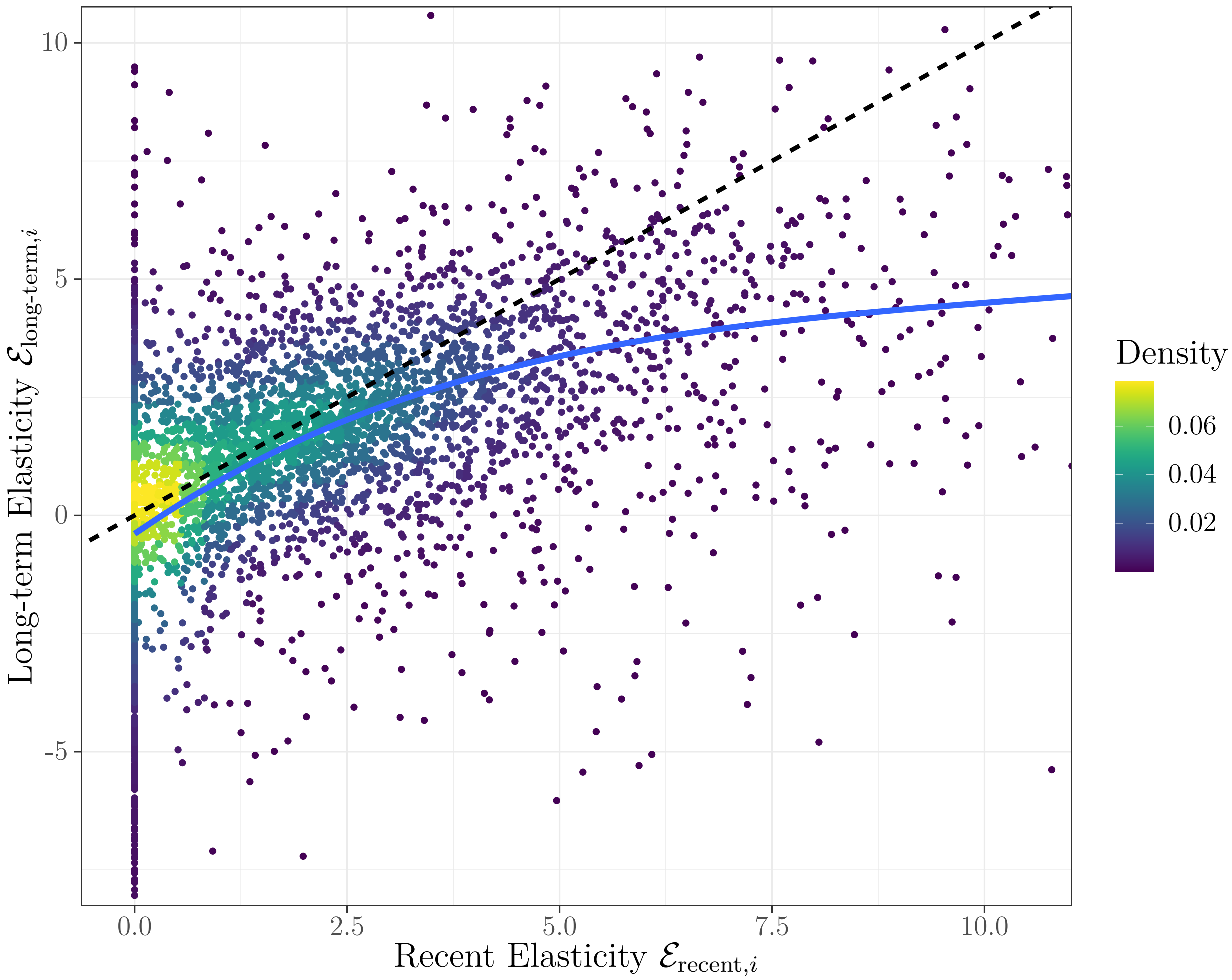


Figure 2. Estimates for elasticities $\mathcal{E}_{\text{recent},i}$ and $\mathcal{E}_{\text{long-term},i}$
Figure 2 shows a scatterplot of elasticity estimates for elasticities to price changes over the past quarter, $\mathcal{E}_{\text{recent},i}$, on the x-axis, and variation over the three preceding quarters, $\mathcal{E}_{\text{long-term},i}$, on the y-axis. Each dot represents one institutional investor in the sample. The solid blue line is a fitted trend line based on cubic regression, and the black dashed line represents flat term structures of elasticities, $\mathcal{E}_{\text{long-term},i} = \mathcal{E}_{\text{recent},i}$. Dots below the dashed line are institutions with downward-sloping term structures of elasticities. The estimation equation is equation (19).

institutions in this corner of the figure include large institutional asset managers such as Fidelity, with elasticities close to zero across horizons (Haddad, Huebner, and Loualiche, 2022). Notably, the residual household sector also falls into this sector.

To the right of a real-time elasticity of 2.5, the trend line diverges from slope 1. Such institutions, on average, have downward-sloping elasticity term structures with $\mathcal{E}_{\text{long-term},i} < \mathcal{E}_{\text{recent},i}$. This class of institutions broadly captures arbitrageurs, who are initially willing to respond very elastically to shocks. Subsequently, they are less inclined to do so, as captured by their downward-sloping term structures of elasticity. In section 4.2, I show that this behavior is a major driver of momentum in the cross-section of stocks.

As of Q1 2016, about a third of institutions have elasticities above 2.5, representing about 48% of assets under management and including large asset management firms such as Citadel LLC or Berkshire Hathaway. Another example of an institution in this space is AQR Capital Management, one of the strongest proponents of factor investing. It is particularly active in the areas of value- and momentum investing.[46] As a value investor, AQR seeks to overweight cheap and underweight expensive stocks: when a stock becomes cheap, AQR wants to hold more of it. Such a contrarian strategy can be expressed through a high price elasticity of demand. Indeed, AQR has a real-time elasticity $\mathcal{E}_{\text{recent}}$ of 4.15, which in Q1 2016 corresponds to the 85^{th} percentile in the cross-section of institutions. Conversely, AQR is also a strong proponent of momentum investing, as represented through longer-term elasticities lower than recent elasticities. Consistent with this, AQR's difference between recent and long-term elasticity, $\mathcal{E}_{\text{long-term}} - \mathcal{E}_{\text{recent}}$, is about -1.25, corresponding to the 25^{th} percentile across institutions.

Table 2 shows time-series averages of cross-investor summary statistics for recent elasticities $\mathcal{E}_{\text{recent}}$ and differences between the recent and long-term elasticity, $\mathcal{E}_{\text{long-term}} - \mathcal{E}_{\text{recent}}$. Time-series variation of these measures is purely driven by changes in investor composition, as I estimate one recent and one longer-term elasticity for each investor, similar to Koijen, Richmond, and Yogo (2020).

Median and average recent elasticities are about $1.3 - 1.9$, which is substantially higher than constant elasticity estimates from previous asset-demand systems by a factor of about 3 (Koijen and Yogo, 2019; Gabaix and Koijen, 2020; Haddad, Huebner, and Loualiche, 2022),[47] but in line with some estimates from other research designs (e.g., Pavlova and Sikorskaya,

[46] https://www.aqr.com/Insights/Systematic-Investing

[47] A notable exception is van der Beck (2022), who also uses flow-based identification to find similar magnitudes for elasticities.

Table 2. Summary statistics for the term structure of elasticities $\mathcal{E}_{\textbf{long-term}} - \mathcal{E}_{\textbf{recent}}$

	$\mathcal{E}_{\text{recent}}$	$\mathcal{E}_{\text{long-term}} - \mathcal{E}_{\text{recent}}$
Average	1.93	−0.55
Standard Deviation	2.35	2.12
Quantile 10%	0.00	−2.86
Quantile 25%	0.00	−1.40
Quantile 33%	0.30	−0.97
Median	1.31	−0.33
Quantile 67%	2.29	0.25
Quantile 75%	2.92	0.59
Quantile 90%	4.77	1.52

Table 2 reports summary statistics for the cross-institution distribution of recent elasticities, $\mathcal{E}_{\text{recent}}$, and the term structure of elasticities, $\mathcal{E}_{\text{long-term}} - \mathcal{E}_{\text{recent}}$, based on estimates of the model described in equation (19) using data between 1999 and 2020.

2022).[48] Yet all these are at least three orders of magnitude below the elasticity implied from a standard frictionless model (Petajisto, 2009).[49] Around 25% of investors have recent elasticity $\mathcal{E}_{\text{recent}}$ equal to zero.[50] On the other side, about 10% of investors have elasticities above 5.

The difference between recent and long-term elasticity captures the term structure of elasticities and can drive momentum. When investors are initially willing to trade against a shock but subsequently leave, the initial price impact of the shock has to increase in equilibrium. This channel is represented through $\mathcal{E}_{\text{long-term}} - \mathcal{E}_{\text{recent}} < 0$, meaning that investors'

[48]See Gabaix and Koijen (2020) for a detailed summary of elasticity estimates from the literature.

[49]Davis, Kargar, and Li (2022) argue that information frictions among uninformed investors can rationalize inelastic demand curves.

[50]The estimation procedure imposes that recent elasticities $\mathcal{E}_{\text{recent}}$ have to be non-negative, as otherwise, the existence of equilibrium in the counterfactuals of section 4.1 would not be guaranteed (Koijen and Yogo, 2019).

initial response to a shock $\mathcal{E}_{\text{recent}}$ is more pronounced than their response $\mathcal{E}_{\text{long-term}}$ to a past shock, corresponding to a downward-sloping term structure of elasticities. The cross-sectional average and median differences across investors are about -0.33 to -0.5, meaning investors' responses to past shocks are typically about 25% weaker than their immediate responses.

There is substantial heterogeneity across investors in how they respond to prices dynamically. On one end of the spectrum, there are investors with a steeply decreasing term structure of elasticities. For example, the fraction of investors whose elasticity to longer-term variation in prices is lower than that to recent variation in prices, by at least 1, is about 33%. On the other end of the spectrum, there are about 15% of investors whose long-term elasticity is higher than their recent elasticity by at least 1.

3.4.1 Estimates aggregated on stock level

Above I have argued that there is a large degree of heterogeneity in investors' term structure of demand elasticities. I use this variation in section 4.2, combined with cross-sectional variation in the ownership of stocks. As a result, individual investor heterogeneity aggregates up to stock-level heterogeneity. This source of variation allows me to predict where momentum should be the strongest.

More precisely, I aggregate investor-level recent and longer-term elasticities into an aggregate stock-level elasticity term structure, equivalent to equations (14) and (15):

$$\bar{\mathcal{E}}_{\text{recent},t}(n) \equiv \sum_i o_{it}(n)\mathcal{E}_{\text{recent},i} \tag{28}$$

$$\bar{\mathcal{E}}_{\text{long-term},t}(n) \equiv \sum_i o_{it}(n)\mathcal{E}_{\text{long-term},i} \tag{29}$$

$$\eta_t(n) \equiv \frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}}{\bar{\mathcal{E}}_{\text{recent},t}} \tag{30}$$

Here the ownership share $o_{it}(n)$ captures the proportion of shares investor i holds of stock n at time t, such that $\bar{\mathcal{E}}_{\text{recent},t}(n)$ and $\bar{\mathcal{E}}_{\text{long-term},t}(n)$ are the ownership-weighted average

Table 3. Aggregate term structures of elasticities and stock characteristics

	Recent Elasticity	Elasticity Term Structure
	(1)	(2)
Log Market Capitalization	0.711***	0.269***
	(0.018)	(0.020)
Log Book Equity	-0.120***	0.044*
	(0.017)	(0.020)
Profitability	0.121***	0.163***
	(0.008)	(0.010)
Investment	0.007	-0.015**
	(0.005)	(0.005)
Dividend Yield	-0.210***	-0.111***
	(0.012)	(0.010)
Date Fixed Effects	Yes	Yes
N	257,941	257,941
R^2	0.395	0.139

Table 3 reports coefficient estimates from panel regression of elasticities onto stock characteristics: log market capitalization, log book equity, profitability, investment, and dividend yield. The dependent variables are the aggregate recent elasticity, $\bar{\mathcal{E}}_{\text{recent},t}(n)$, in the first column and the aggregate term structure of elasticities, $\eta_t(n)$, in the second column. All variables, including elasticities, are cross-sectionally demeaned and standardized at each date. Both specifications include date-fixed effects. The sample period is between 1999 and 2000. Standard errors are 2-way clustered by date and stock.

recent and longer-term elasticities for stock n at time t, respectively. The variable $\eta_t(n)$ then captures the the stock's aggregate term structure of elasticities, like in section 2.

Table 3 provides the results of panel regressions of aggregate real-time elasticities $\bar{\mathcal{E}}_{\text{recent},t}(n)$ and term structures of elasticities $\eta_t(n)$ onto stock characteristics.

Stocks with a log market capitalization of one standard deviation above average have recent elasticities $\bar{\mathcal{E}}_{\text{recent}}$ that are 0.7 standard deviations above average. This is consistent with the idea that large stocks are more liquid, a typical result in the asset-demand system literature, as liquidity and elasticities are conceptually related (Koijen and Yogo, 2019; Haddad, Huebner, and Loualiche, 2022). Beyond size, elastic stocks tend to be profitable and have a low dividend yield.

Similarly, stocks with one standard deviation higher log market capitalization tend to have about 0.25 standard deviations more upward-sloping elasticity term structures. And again, profitable stocks tend to have increasing elasticity term structures, while high dividend-yield stocks tend to have more decreasing term structures.

4 Implications for the making of momentum

4.1 Decomposing momentum returns

In this section, I provide a positive account of momentum returns between 1999 and 2020; I decompose momentum into how much results from the persistence of demand shocks and how much is due to the term structure of demand elasticities. This is where the asset demand system provides unique insights due to its ability to account for equilibrium. In the demand system, observed prices at each point in time are the equilibrium of the individual behavior of all investors. In other words, by taking all components of the demand system — stock characteristics (excluding recent equilibrium returns), parameter estimates from the demand system, including residual latent demand $\epsilon_{it}(n)$, and investor assets — one can reconstruct the market-clearing equilibrium stock price or equivalently, the equilibrium stock return. Next, I evaluate each component's role in the demand system by tracing their evolution from time $t-1$ to time t, solving for the counterfactual market clearing price at each step, and combining them into counterfactual momentum portfolio returns based on classic momentum sorts. This procedure allows me to isolate the relative contributions to the aggregate momentum performance of all three components, answering the question of what momentum returns would have been if only one of the components had been present.

More formally, I follow Koijen and Yogo (2019) in defining a function $\mathbf{g}$ that maps time-invariant demand system estimates $\theta \equiv \{\mathcal{E}_{\text{recent},i}, \mathcal{E}_{\text{long-term},i}, \underline{d}_{1i}\}_{\forall i}$, longer-term price changes $\mathbf{p_{t-1}} - \mathbf{p_{t-4}}$, exogenous stock characteristics $\mathbf{X_t}$, and unobserved latent demand $\boldsymbol{\epsilon}_\mathbf{t}$ extracted from the demand system to the market clearing equilibrium price, based on equation (21).[51] In other words, the function $\mathbf{g}$ determines the equilibrium price p_t that is consistent with individual demand (19), the assets-under-management dynamics (20), and the equilibrium condition (21).

Equation (31) shows that observed returns are the difference in market clearing prices based on the demand system, which is true by definition of the estimated demand system:

$$\mathbf{p_t} - \mathbf{p_{t-1}} = \mathbf{g}\left(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}, \mathbf{X_t}, \epsilon_\mathbf{t}; \theta\right) - \mathbf{g}\left(\mathbf{p_{t-2}} - \mathbf{p_{t-5}}, \mathbf{X_{t-1}}, \epsilon_\mathbf{t-1}; \theta\right) \tag{31}$$

$$= \Delta\mathbf{p_t}(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}) + \Delta\mathbf{p_t}(\mathbf{X}) + \Delta\mathbf{p_t}(\epsilon) \tag{32}$$

Crucially, the demand system allows me to trace the contribution of each term: long-term past returns, stock characteristics, and latent demand, as shown in equation (32). That is, I update each component of the demand system step-by-step and calculate its counterfactual returns:

$$\Delta\mathbf{p_t}(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}) = \mathbf{g}\left(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}, \mathbf{X_{t-1}}, \epsilon_\mathbf{t-1}; \theta\right) - \mathbf{g}\left(\mathbf{p_{t-2}} - \mathbf{p_{t-5}}, \mathbf{X_{t-1}}, \epsilon_\mathbf{t-1}; \theta\right) \tag{33}$$

$$\Delta\mathbf{p_t}(\mathbf{X}) = \mathbf{g}\left(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}, \mathbf{X_t}, \epsilon_\mathbf{t-1}; \theta\right) - \mathbf{g}\left(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}, \mathbf{X_{t-1}}, \epsilon_\mathbf{t-1}; \theta\right) \tag{34}$$

$$\Delta\mathbf{p_t}(\epsilon) = \mathbf{g}\left(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}, \mathbf{X_t}, \epsilon_\mathbf{t}; \theta\right) - \mathbf{g}\left(\mathbf{p_{t-1}} - \mathbf{p_{t-4}}, \mathbf{X_t}, \epsilon_\mathbf{t-1}; \theta\right). \tag{35}$$

Up to this point, I followed Koijen and Yogo (2019) for the definition of counterfactual returns. But next, I form counterfactual momentum portfolio returns to assess which components are responsible for momentum in equilibrium.[52] In particular, I perform standard

[51]There are more components to the demand system, for example, flows to institutions. However, they empirically do not contribute to the making of momentum, so they have been omitted for brevity. The irrelevance of the assets-under-management process is consistent with Davis and Azarmsa (2023), who find that asset demand elasticities are set at the intermediary level rather than by households allocating funds across institutions.

[52]In a contemporary paper, Tamoni, Sokolinski, and Li (2022) use a similar technique to decompose the returns of a large set of anomalies, which comes with a tradeoff: The benefit of their approach is that it

Table 4. Decomposition of momentum returns

Momentum	Decomposition		
Annualized Return (1999-2020)	Elasticities	Fundamentals	Demand Shocks
2.09%	24.65%	22.11%	−44.67%

Table 4 decomposes total annualized momentum returns between 1999 and 2020 into contributions from the term structure of demand elasticities in column 2, the evolution of demand for fundamentals in column 3, and the persistence of demand shocks in column 4. All reported numbers represent annualized momentum returns.

momentum sorts as of time $t-1$, meaning that I sort stocks into tercile portfolios based on their performance during the formation period, 2 to 12 months before $t-1$. Then, within each momentum-signal tercile, I calculate value-weighted portfolio returns and calculate the long-short of past winners minus past losers between $t-1$ and t. Specifically, based on $t-1$ momentum sorts, I construct long-short returns based on the observed capital gains $\Delta \mathbf{p_t}$ — observed momentum — but also for each of $\Delta \mathbf{p_t}(\mathbf{p_{t-1}} - \mathbf{p_{t-4}})$, $\Delta \mathbf{p_t}(\mathbf{X})$, and $\Delta \mathbf{p_t}(\epsilon)$, corresponding to the portion of momentum driven by the term structure of demand elasticities, fundamentals, and demand shocks, respectively.

Table 4 implements the decomposition. First, the term structure of demand elasticities is the primary driver of momentum between 1999 and 2020. On its own, it would have generated annualized momentum returns of about 24%. Investors, in aggregate, are more responsive to recent returns than longer-term variation in prices. They respond relatively more elastically to a shock over a horizon of one quarter, limiting its impact on prices. However, as investors subsequently become less willing to continue to absorb the shock, its equilibrium price impact increases, creating momentum.

Second, investors' price-inelastic baseline demand, loosely defined as encapsulating the dynamics of fundamentals and the evolution of investors' latent demand, are generally mean-reverting, capturing overreaction rather than underreaction. They result in return reversal

is broader in scope, the cost that it is potentially missing additional aspects of investors' trading strategies that can matter for some anomalies, for example, the term structure of demand elasticities for price-based anomalies like momentum.

that undoes most momentum originating from the term structure of elasticities. While potentially surprising, this result is in line with evidence from Koijen and Yogo (2019): Investing in potentially undervalued stocks with low latent demand and shorting potentially overvalued stocks with high latent demand is profitable, consistent with the idea of mean-reversion in investor demand.

These results are broadly consistent with momentum being a buildup anomaly (van Binsbergen et al., 2023), meaning momentum traders further exacerbate mispricings through their dynamic trading against prices. This mechanism differs from a resolution anomaly, where anomaly returns would represent a correction of mispricings, consistent with theories behind persistent demand shocks, like underreaction.[53]

We can further split the impact of baseline demand into the part coming from unobserved demand shocks and the demand for stock characteristics. The component capturing momentum from fundamentals strongly contributes toward momentum. There are multiple explanations. For example, this behavior could result from fundamental stock characteristics drifts, such as earnings momentum (Chordia and Shivakumar, 2006). But then rational investors should consider such drifts in fundamentals when forming their beliefs. An alternative explanation is that the demand for characteristics and latent demand are related, generating a specific form of underreaction. In particular, the observed behavior is consistent with past latent demand predicting future stock characteristics that enter investors' demand functions: In the demand system, this mechanism generates both mean-reversion in latent demand and momentum due to investors' demand for stock characteristics. Overall, however, mean reversion prevails. This pattern is consistent with institutional attention predicting market returns around news announcements (Da et al., 2023) and broadly in line with recent evidence on the role of fundamentals and risk in explaining momentum and reversal (e.g., Novy-Marx, 2015; Kelly, Moskowitz, and Pruitt, 2021), especially to the extent that fundamentals capture

[53]While the language of persistent demand shocks from underreaction versus a downward-sloping term structure of demand elasticities aligns with the distinction between buildup and resolution anomalies, this is not necessarily the case for any source of persistent demand shocks. For example, theories of delayed underreaction typically fit that of buildup anomalies despite working through persistent demand shocks.

stock characteristics.

Put together, overall momentum returns during the sample period were low at about 2% per year. The demand system allows thinking through candidate mechanisms in a structured way, even without a longer time series: One potential explanation is anomaly attenuation (Chordia, Subrahmanyam, and Tong, 2014). Investors might have learned about underreaction, leading to less (positively) persistent demand and, thereby, to more informationally efficient markets and less momentum. There is some corroborating evidence. For example, Martineau (2021) shows that the post-earnings announcement drift (e.g., Bernard and Thomas, 1989, 1990), an example of underreaction, has recently disappeared.[54] Structural changes in asset ownership might have also played a role. For example, Baltussen, van Bekkum, and Da (2019) show that stock market serial dependence has decreased in response to the secular rise of indexing. A potential mechanism is that passive investors are inelastic across horizons (Haddad, Huebner, and Loualiche, 2022), so their increasing presence has flattened the aggregate term structure of demand elasticities, weakening momentum.[55] This is despite passive investing leading to more volatility (e.g., Ben-David, Franzoni, and Moussawi, 2018). However, the recent past could also have just been bad luck for momentum; they have been subject to some of the most severe momentum crashes à la Daniel and Moskowitz (2016).

4.2 Demand-system enhanced momentum returns

In the previous section, I showed that the dynamic evolution of investors' responses to demand shocks is the primary driver of momentum in the cross-section of stock returns. If the model is correctly specified, cross-sectional variation in aggregate term structures of demand elasticities across stocks directly translates to variation in momentum profitability. However,

[54]Ben-Rephael, Da, and Israelsen (2017) find that institutional investors exhibit less underreaction around news events than retail investors, suggesting that increased institutional ownership over time might have weakened aggregate underreaction.

[55]On the style level, Ben-David et al. (2023) show that a Morningstar reform reduced positive feedback trading, leading to less style-level momentum. In the language of my framework, less positive feedback trading is represented through a flatter term structure of demand elasticities.

suppose the instrumented local variation used to identify investors' term structure of demand elasticities is structurally different from the average variation in the data.[56] In that case, the unconditional relation between momentum profitability and investors' aggregate term structures might be weak. Therefore, I verify the unconditional relation in the data: I use my demand-system estimates to form both a "demand-system enhanced" momentum strategy excluding stocks less prone to exhibit momentum, and a strategy combining momentum and reversal based on the slope of the term structure of demand elasticities.

More precisely, I use cross-sectional variation in stock ownership across stocks to predict in which stocks momentum strategies are most profitable.[57][58] In stocks disproportionally held by momentum-generating investors, that is, investors with downward-sloping term structure of elasticities, the price impact of past shocks gets exacerbated over time. This generates positive serial correlation in stock returns and, thus, stock momentum.

I sort stocks in the cross-section based on their aggregate elasticity term structure $\eta_t(n)$ from section 3.4.1, and then test if momentum strategies' profitability varies based on these sorts. In the context of Table 5, I first sort stocks into two categories based on whether they are above or below the time t cross-sectional median of aggregate stock-level term structures of elasticities, $\eta_t(n)$. Then, within each category, I separately implement momentum strategies. That is, I sort stocks into terciles based on past performance between months $t-12$ to $t-1$,

[56] This constitutes a Lucas critique: investors' demand elasticities might not be deep structural parameters but depend on the type of variation and institutional context. For example, Haddad, Huebner, and Loualiche (2022) show that in the cross-section of stocks, the same investor behaves differently depending on stock characteristics and the set of other institutional investors present.

[57] Variation from the ownership distribution of stocks is not exogenous. Focusing on such variation comes at the cost of less tight identification, but is meant to provide complementary evidence and to get toward external validity.

[58] There are many examples of the importance of ownership structure for returns: Gompers and Metrick (2001) argue that the attenuation of the size premium is partially driven by institutional ownership. Antón and Polk (2014) show that common stock ownership affects stock return correlations. Rzeźnik and Weber (2022) demonstrate that fire sales only generate price pressure in the absence of specialized investors. Cremers and Pareek (2015) find that momentum is stronger in stocks held by institutions with less persistent investment universe. While the presence of short-term investors is related to the downward-sloping term structure of elasticities, the latter is more narrowly defined in that it works only through short-term contrarian behavior. More generally, intermediary ownership drives returns (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017; Kargar, 2021), especially for heavily intermediated asset classes (Haddad and Muir, 2021; Eisfeldt et al., 2022).

Table 5. Momentum returns sorted by term structure of elasticities η

All Stocks	Low η	High η	Lo−Hi	All Stocks	Low η	High η	Lo−Hi
Average Returns: Value Weighted				Average Returns: Equally Weighted			
2.09	6.11	−0.72	6.82**	1.87	3.87	0.08	3.79**
(4.04)	(4.26)	(4.31)	(3.43)	(4.41)	(4.62)	(4.23)	(1.77)
Fama-French 3 Factor α: Value Weighted				Fama-French 3 Factor α: Equally Weighted			
5.51*	10.09***	2.45	7.64**	5.33	7.33*	3.77	3.56**
(3.07)	(2.98)	(3.88)	(3.68)	(3.76)	(3.99)	(3.56)	(1.81)
Carhart 4 Factor α: Value Weighted				Carhart 4 Factor α: Equally Weighted			
0.40	4.86	−2.16	7.03*	0.41	2.16	−0.83	2.98
(1.82)	(3.56)	(1.76)	(4.07)	(1.57)	(2.31)	(1.24)	(2.07)

Table 5 reports the returns to momentum strategies, where the long leg consists of the tercile of winners during the formation period and the short leg of the tercile of losers during the formation period. The four left columns report the returns to value-weighted momentum portfolios, while the four right columns use equal weighting. Columns 1 and 5 look at the performance of momentum among all stocks. Columns 2 and 6 filter to stocks with a term structure of elasticity η that is more steeply decreasing than the cross-sectional median. Columns 3 and 7 use stocks not used in columns 2 and 6, and columns 4 and 8 report their difference. The first panel reports average returns, while the second and third panels show the anomaly α with respect to the Fama and French (1993) and Carhart (1997) factor models. The sample period is from 1999 to 2020. Standard errors are estimated using Newey-West with 12 lags. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively.

and build portfolios that go long past winners, and short past losers.

Columns 1 to 4 of Table 5 exhibit returns to momentum strategies that value-weight both the long and short legs, while columns 5 to 8 equal-weight returns. The first and fourth columns show returns to a standard momentum strategy in all stocks, irrespective of their term structure of elasticities. Momentum returns are generally for the sample period from October 1999 to December 2020: Momentum returns range from an annualized 0 to 6%, depending on whether they are value- or equal weighted, and on whether they average returns or α with respect to standard factor models. These low momentum returns are generally consistent with ideas of anomaly attenuation as in Chordia, Subrahmanyam, and

Tong (2014).

However, there is substantial variation in momentum returns based on cross-sectional variation in the aggregate term structure of demand elastiticies $\eta_t(n)$: Momentum returns are more pronounced in stocks with more downward-sloping term structure of elasticities (columns 2 and 6) relative to momentum returns based on the entire universe of stocks by an annualized 4% value-weighted (2% equal-weighted). Consistent with this, momentum returns are only economically and statistically significant within low η stocks after controlling for risk as captured by the Fama-French 3 Factor model (Fama and French, 1993). This corresponds to the idea of an "enhanced momentum strategy": Instead of implementing a momentum strategy based on the entire universe of stocks, limiting the universe of stocks to those that are more prone to exhibit momentum – stocks with a steeply downward-sloping term structure of demand elasticities – produces superior risk-adjusted performance.

Across specifications, stocks with low η, i.e., stocks with more downward-sloping term structure of elasticities, have higher momentum returns than stocks with flat or upward-sloping term structure by about 7% value-weighted (column 4), and 3.5% equally weighted (column 8). Appendix Table IA.2 shows the robustness of these results in a battery of additional tests involving variations on the construction of momentum and term-structure portfolios, and short-sales constraints and size controls, which are designed to capture issues related to illiquidity.[59] Moreover, these Lo-Hi differences remain constant irrespective of the choice of factor model they are evaluated against. This finding suggests a new strategy: Going long momentum in low η stocks and going short momentum in high η stocks, which are expected to feature reversal rather than momentum. Conceptually, this idea is combining

[59] First, illiquidity and informational efficiency are particularly relevant for small stocks (Lo and MacKinlay, 1990; Jegadeesh and Titman, 1993; Lakonishok, Shleifer, and Vishny, 1994; Hong, Lim, and Stein, 2000). To see the impact of small stocks, one of the robustness checks in Appendix Table IA.2 looks at the profitability of momentum across the size distribution and shows that my results are robust to conditioning on size. Second, Haddad, Huebner, and Loualiche (2022) show that elasticities are empirically related to measures of liquidity: stocks with low elasticities tend to be more illiquid. This raises the concern that dividing by the aggregate real-time elasticity in equation (28) emphasizes illiquid stocks. Consequently, one of the robustness checks in Appendix Table IA.2 considers sorting on the absolute instead of the relative difference between $\bar{\mathcal{E}}_{\text{recent},t}(n)$ and $\bar{\mathcal{E}}_{\text{long-term},t}(n)$, which does not affect results.

elements of momentum and reversal strategies. In fact, it is equivalent to combining a momentum strategy in low η "momentum stocks" that are expected to exhibit momentum because of a downward-sloping term structure of demand elasticities with a reversal strategy in high η "reversal stocks" that are expected to exhibit reversal for upward-sloping term structures. However, unlike, for example, Asness, Moskowitz, and Pedersen (2013), who combine momentum with long-term reversal, I separate stocks based on their momentum- or reversal properties at the same horizon. Strikingly, the performance of this combined momentum- and reversal strategy is robust to frictions related to short-selling. In particular, a long-only implementation going long past winners in low η momentum stocks and also long past losers in high η reversal stocks generates positive α (Specification (4) in Appendix Table IA.2), despite recent evidence that the performance of many anomalies is concentrated in its short legs (e.g., Muravyev, Pearson, and Pollet, 2022).

The finding that the difference in returns of momentum strategies between stocks with more or less steeply downward-sloping term structure of demand elasticities remains constant across choices of factor models is particularly striking in the context of the Carhart 4 factor model (Carhart, 1997), which contains a momentum factor. This suggests that the variation in momentum strategy returns based on the term structures is not merely the result of recovering stocks with high β_{Mom}, that is, a high factor-beta with respect to the momentum factor, but instead can point at variation in momentum profitability that remains unspanned by the momentum factor itself. Specifically, the factor-beta of the Lo-Hi strategy, or equivalently, the difference in momentum factor exposures between momentum strategies in low versus high η stocks, is close to zero, at $\beta_{Mom} = 0.12$.

Momentum strategies are known to suffer from momentum crashes (Daniel and Moskowitz, 2016), periods during which momentum performs exceptionally poorly. If the high returns of the proposed enhanced momentum strategy were driven by high factor-betas with respect to the momentum factor, then the strategy would necessarily suffer from momentum crashes as well. In fact, its momentum crashes would be proportionally more severe.

As it is, that need not be the case. Below, I examine the performance of the proposed enhanced strategies during times when traditional momentum strategies crash.

4.2.1 Momentum crashes

Daniel and Moskowitz (2016) identify two prolonged periods they label momentum crashes, following the Great Depression (June 1932 to December 1939) and the 2008-2009 financial crisis (March 2009 to March 2013). I study the performance of enhanced momentum strategies during the latter of these two momentum crashes.[60]

Table 6 is equivalent to Table 5, but zooms into the momentum crash period from March 2009 to March 2013. Columns 1 and 4 show that average annualized momentum returns based on the full universe of stocks were low, at about -7.5% equal-weighted and -9% value-weighted. Accounting for factor exposures accounts for most of this negative performance.

Implementing a momentum strategy in low elasticity term structure stocks would have largely avoided the momentum crash. Most strikingly, the gap in momentum performance between low and high η stocks during momentum crashes is particularly wide at an annualized $9-12.5\%$ value-weighted and 7.5% equal-weighted across specifications.

Since momentum crashes typically occur immediately following stock market crashes, they likely coincide with high marginal utility states. This would suggest that unconditional outperformance of momentum in low η stocks could be fully consistent with rational explanations as compensation for momentum-crash-related risk if low η stocks would suffer from particularly strong momentum crashes. Instead, the opposite is the case. Low term-structure of elasticity stocks do not only have larger momentum returns unconditionally; they even have larger momentum returns during times when marginal utility is likely to be high. Relatedly, Daniel and Moskowitz (2016) show that this is true for momentum returns more generally,

[60]One caveat for the results of this section is that I study the only large momentum crash that occurred during my already relatively short sample period. Consequently, results may not be representative of other momentum crashes. Nevertheless, as Table 6 shows, the difference between momentum performance in low- and high-term-structure of elasticity stocks is strongly statistically significant, despite the short sample period.

Table 6. Momentum returns sorted by term structure of elasticities η during the March 2009 to March 2013 momentum crash

All Stocks	Low η	High η	Lo−Hi	All Stocks	Low η	High η	Lo−Hi
Average Returns: Value Weighted				Average Returns: Equally Weighted			
−8.97	−3.48	−12.35	8.88***	−7.61	−3.85	−11.19	7.33***
(11.94)	(11.45)	(11.55)	(3.06)	(14.84)	(14.28)	(15.10)	(1.97)
Fama-French 3 Factor α: Value Weighted				Fama-French 3 Factor α: Equally Weighted			
−0.45	7.39	−5.17	12.56***	−1.16	3.26	−4.57	7.82***
(6.05)	(5.60)	(6.46)	(4.36)	(8.85)	(8.94)	(8.60)	(1.83)
Carhart 4 Factor α: Value Weighted				Carhart 4 Factor α: Equally Weighted			
2.23	10.01**	−2.83**	12.84***	1.27	5.43	−1.97	7.40***
(2.51)	(4.60)	(1.11)	(4.74)	(3.18)	(4.09)	(2.31)	(2.29)

Table 6 reports the returns to momentum strategies from March 2009 to March 2013, a momentum crash period identified by Daniel and Moskowitz (2016). Besides filtering to a period of momentum crashing, the construction of the table is equivalent to table 5: The left four columns report the returns to value-weighted momentum portfolios, while the right four columns use equal weighting. Columns 1 and 5 look at the performance of momentum among all stocks. Columns 2 and 6 filter to stocks with a term structure of elasticity η that is more steeply decreasing than the cross-sectional median. Columns 3 and 7 use stocks not used in columns 2 and 6, and columns 4 and 8 report their difference. The first panel reports average returns, while the second and third panels show the anomaly α with respect to the Fama and French (1993) and Carhart (1997) factor models. The sample period is from March 2009 to March 2013. Standard errors are estimated using Newey-West with 12 lags. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively.

as crashes are partially predictable, such that timing momentum improves performance.[61]

5 Conclusion

Momentum in stock returns is one of the most widely studied anomalies, with many papers proposing explanations for momentum based on some form of underreaction. In this paper, I emphasize the role of a complementary channel: the term structure of demand elasticities,

[61] Similarly, Burnside et al. (2011) show that peso problems cannot fully explain the performance of currency carry trades because carry remains profitable after hedging out extreme disaster risk.

representing investors differential responses to short- and longer-term price variation. I put forward a framework incorporating both the direct evolution of demand shocks over time and investors' dynamic reactions to price changes across horizons. Finally, I estimate the model for institutional investors in the U.S. stock market between 1999 and 2020.

My estimates suggest that the main driver of momentum returns is the downward-sloping term structure of elasticities. On average, investors are 25% less responsive to longer-term variation in prices than to recent price changes over the previous quarter. Institutions exceptionally responsive to recent price changes drive this overall pattern. In contrast, demand shocks exhibit mean reversion and thus generate reversal.

While this evidence is inconsistent with momentum from underreaction in a literal sense, behavioral biases might play a slightly different role than suggested by existing theories by instead working through how investors interact with prices. My results, therefore, indicate the need to incorporate investors' dynamic price responses into models of momentum generation.

Yet, beyond the application in this paper, differential responses to price changes that are more nuanced across horizons could also help us understand a larger class of price-based anomalies in a unified framework. For example, besides momentum, there are short-term and long-term reversals. A rich term structure of elasticities could reproduce such time-series patterns through a term structure that is upward-sloping at short, downward-sloping at intermediate, and upward-sloping at long horizons. Moreover, a more granular term structure of elasticities can also address practical questions like: What is the best way to implement a momentum strategy? What is the optimal formation period? And does the answer vary on the stock level? And finally, understanding the intensity of arbitrage across horizons can have important implications for financial fragility. For example, do investors step in during a fire sale to provide liquidity or exacerbate the initial shock? How does the answer change as the fire sale progresses? The term structure of demand elasticities provides an answer to these questions.

References

Adam, Klaus and Stefan Nagel. 2022. "Expectations Data in Asset Pricing." Tech. rep., National Bureau of Economic Research.

Adrian, Tobias, Erkko Etula, and Tyler Muir. 2014. "Financial Intermediaries and the Cross-Section of Asset Returns." *The Journal of Finance* 69 (6):2557–2596.

Angrist, Joshua D and Alan B Krueger. 1992. "The effect of age at school entry on educational attainment: an application of instrumental variables with moments from two samples." *Journal of the American statistical Association* 87 (418):328–336.

Antón, Miguel and Christopher Polk. 2014. "Connected Stocks." *The Journal of Finance* 69 (3):1099–1127.

Arellano, Manuel and Costas Meghir. 1992. "Female Labour Supply and On-the-Job Search: An Empirical Model Estimated Using Complementary Data Sets." *The Review of Economic Studies* 59 (3):537–559.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen. 2013. "Value and Momentum Everywhere." *The Journal of Finance* 68 (3):929–985.

Atmaz, Adem, Stefano Cassella, Huseyin Gulen, and Fangcheng Ruan. 2022. "Contrarians, Extrapolators, and Stock Market Momentum and Reversal." Tech. rep.

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

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

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

Baltussen, Guido, Sjoerd van Bekkum, and Zhi Da. 2019. "Indexing and stock market serial dependence around the world." *Journal of Financial Economics* 132 (1):26–48.

Barardehi, Yashar H, Vincent Bogousslavsky, and Dmitriy Muravyev. 2023. "What drives momentum and reversal? evidence from day and night signals." Tech. rep.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer. 2015. "X-CAPM: An extrapolative capital asset pricing model." *Journal of Financial Economics* 115 (1):1–24.

———. 2018. "Extrapolation and Bubbles." *Journal of Financial Economics* 129 (2):203–227.

Barberis, Nicholas and Andrei Shleifer. 2003. "Style investing." *Journal of Financial Economics* 68 (2):161–199.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. 1998. "A model of investor sentiment." *Journal of Financial Economics* 49 (3):307–343.

Bastianello, Francesca and Paul Fontanier. 2021. "Partial Equilibrium Thinking in General Equilibrium." Tech. rep., Harvard.

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

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song. 2023. "Discontinued Positive Feedback Trading and the Decline of Return Predictability." *Journal of Financial and Quantitative Analysis* :163.

Ben-Rephael, Azi, Zhi Da, and Ryan D Israelsen. 2017. "It depends on where you search: Institutional investor attention and underreaction to news." *The Review of Financial Studies* 30 (9):3009–3047.

Berk, Jonathan B. and Richard C. Green. 2004. "Mutual Fund Flows and Performance in Rational Markets." *Journal of Political Economy* 112 (6):1269–1295.

Berk, Jonathan B., Richard C. Green, and Vasant Naik. 1999. "Optimal Investment, Growth

Options, and Security Returns." *The Journal of Finance* 54 (5):1553–1607.
Bernard, Victor L. and Jacob K. Thomas. 1989. "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?" *Journal of Accounting Research* 27:1–36.
———. 1990. "Evidence that stock prices do not fully reflect the implications of current earnings for future earnings." *Journal of Accounting and Economics* 13 (4):305–340.
Betermier, Sebastien, Laurent E Calvet, Samuli Knüpfer, and Jens Soerlie Kvaerner. 2022. "What Do the Portfolios of Individual Investors Reveal About the Cross-Section of Equity Returns?" Tech. rep.
Bordalo, Pedro, Nicola Gennaioli, Rafael LaPorta, and Andrei Shleifer. 2022. "Belief Overreaction and Stock Market Puzzles." Tech. rep., Working paper.
Brandt, Michael W., Pedro Santa-Clara, and Rossen Valkanov. 2009. "Parametric Portfolio Policies: Exploiting Characteristics in the Cross-Section of Equity Returns." *The Review of Financial Studies* 22 (9):3411–3447.
Bretscher, Lorenzo, Lukas Schmid, Ishita Sen, and Varun Sharma. 2020. "Institutional corporate bond pricing." Tech. rep., Swiss Finance Institute Research Paper.
Burnside, Craig, Martin Eichenbaum, Isaac Kleshchelski, and Sergio Rebelo. 2011. "Do Peso Problems Explain the Returns to the Carry Trade?" *Review of Financial Studies* 24 (3):853–891.
Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 2011. "Carry Trade and Momentum in Currency Markets." *Annual Review of Financial Economics* 3 (1):511–535.
Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance." *The Journal of Finance* 52 (1):57–82.
Cassella, Stefano and Huseyin Gulen. 2018. "Extrapolation Bias and the Predictability of Stock Returns by Price-Scaled Variables." *The Review of Financial Studies* 31 (11):4345–4397.
Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok. 1996. "Momentum Strategies." *The Journal of Finance* 51 (5):1681–1713.
Charles, Constantin, Cary Frydman, and Mete Kilic. 2022. "Insensitive Investors." Working paper.
Chaudhry, Aditya. 2022. "Do Subjective Growth Expectations Matter for Asset Prices?" Working paper.
Chen, Hsiu-Lang and Werner De Bondt. 2004. "Style momentum within the S&P-500 index." *Journal of Empirical Finance* 11 (4):483–507.
Chevalier, Judith and Glenn Ellison. 1997. "Risk Taking by Mutual Funds as a Response to Incentives." *Journal of Political Economy* 105 (6):1167–1200.
Chordia, Tarun and Lakshmanan Shivakumar. 2006. "Earnings and price momentum." *Journal of Financial Economics* 80 (3):627–656.
Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong. 2014. "Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?" *Journal of Accounting and Economics* 58 (1):41–58.
Chui, Andy C W, Avanidhar Subrahmanyam, and Sheridan Titman. 2022. "Momentum, Reversals, and Investor Clientele." *Review of Finance* 26 (2):217–255.
Collin-Dufresne, Pierre, Michael Johannes, and Lars A. Lochstoer. 2016. "Parameter Learning in General Equilibrium: The Asset Pricing Implications." *American Economic Review* 106 (3):664–98.
Coval, Joshua and Erik Stafford. 2007. "Asset fire sales (and purchases) in equity markets." *Journal of Financial Economics* 86 (2):479–512. URL `https://www.sciencedirect.com/science/article/pii/S0304405X07001158`.
Cremers, Martijn and Ankur Pareek. 2015. "Short-term trading and stock return anomalies: Momentum, reversal, and share issuance." *Review of Finance* 19 (4):1649–1701.
Da, Zhi, Jian Hua, Chih-Ching Hung, and Lin Peng. 2023. "Market returns and a tale of two types

of attention." Tech. rep.
Da, Zhi, Xing Huang, and Lawrence J. Jin. 2021. "Extrapolative beliefs in the cross-section: What can we learn from the crowds?" *Journal of Financial Economics* 140 (1):175–196.
Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. 1998. "Investor psychology and security market under-and overreactions." *the Journal of Finance* 53 (6):1839–1885.
Daniel, Kent and Tobias J. Moskowitz. 2016. "Momentum crashes." *Journal of Financial Economics* 122 (2):221–247.
Daniel, Kent D, Alexander Klos, and Simon Rottke. 2021. "The dynamics of disagreement." Tech. rep., National Bureau of Economic Research.
Davis, Carter. 2022. "Mispricing and the Elasticity of Quantitative Investment." Working paper.
Davis, Carter and Ehsan Azarmsa. 2023. "Is Asset Demand Elasticity Set at the Household or Intermediary Level?" Tech. rep.
Davis, Carter, Mahyar Kargar, and Jiacui Li. 2022. "An Information-Based Explanation for Inelastic Demand." Working paper.
De Bondt, Werner FM and Richard Thaler. 1985. "Does the stock market overreact?" *The Journal of finance* 40 (3):793–805.
De La O, Ricardo and Sean Myers. 2021. "Subjective Cash Flow and Discount Rate Expectations." *The Journal of Finance* 76 (3):1339–1387.
Dong, Xi, Namho Kang, and Joel Peress. 2022. "Fast and Slow Arbitrage: The Predictive Power of Capital Flows for Factor Returns." Tech. rep.
Dou, Winston, Leonid Kogan, and Wei Wu. 2020. "Common fund flows: Flow hedging and factor pricing." *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper* .
Duffie, Darrell. 2010. "Presidential Address: Asset Price Dynamics with Slow-Moving Capital." *The Journal of Finance* 65 (4):1237–1267.
Egan, Mark, Alexander MacKay, and Hanbin Yang. 2022. "What Drives Variation in Investor Portfolios? Estimating the Roles of Beliefs and Risk Preferences." Tech. rep.
Ehsani, Sina and Juhani T. Linnainmaa. 2022. "Factor Momentum and the Momentum Factor." *The Journal of Finance* 77 (3):1877–1919.
Eisfeldt, Andrea L, Bernard Herskovic, Sriram Rajan, and Emil Siriwardane. 2022. "OTC Intermediaries." *The Review of Financial Studies* .
Fama, Eugene F. 2014. "Two pillars of asset pricing." *American Economic Review* 104 (6):1467–85.
Fama, Eugene F. and Kenneth R. French. 1993. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics* 33 (1):3–56.
Gabaix, Xavier and Ralph SJ Koijen. 2020. "In search of the origins of financial fluctuations: The inelastic markets hypothesis." Mimeo, Harvard University.
Gabaix, Xavier, Ralph SJ Koijen, Federico Mainardi, Sangmin Oh, and Motohiro Yogo. 2022. "Asset Demand of US Households." Mimeo.
Gabaix, Xavier, Arvind Krishnamurthy, and Olivier Vigneron. 2007. "Limits of Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market." *The Journal of Finance* 62 (2):557–595.
Gabaix, Xavier and Matteo Maggiori. 2015. " International Liquidity and Exchange Rate Dynamics." *The Quarterly Journal of Economics* 130 (3):1369–1420.
Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman. 2009. "Demand-Based Option Pricing." *The Review of Financial Studies* 22 (10):4259–4299.
Ghaderi, Mohammad, Mete Kilic, and Sang Byung Seo. 2022. "Learning, slowly unfolding disasters, and asset prices." *Journal of Financial Economics* 143 (1):527–549.
Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus. 2021. "Five facts about beliefs and portfolios." *American Economic Review* 111 (5):1481–1522.

Goetzmann, William N. and Massimo Massa. 2002. "Daily Momentum and Contrarian Behavior of Index Fund Investors." *Journal of Financial and Quantitative Analysis* 37 (3):375389.

Gompers, Paul A. and Andrew Metrick. 2001. "Institutional Investors and Equity Prices." *The Quarterly Journal of Economics* 116 (1):229–259.

Goulding, Christian L, Campbell R Harvey, and Michele Mazzoleni. 2022. "Momentum turning points." Tech. rep.

Greenwood, Robin, Samuel G Hanson, and Gordon Y Liao. 2018. "Asset Price Dynamics in Partially Segmented Markets." *The Review of Financial Studies* 31 (9):3307–3343.

Greenwood, Robin and Andrei Shleifer. 2014. "Expectations of Returns and Expected Returns." *The Review of Financial Studies* 27 (3):714–746.

Greenwood, Robin and Dimitri Vayanos. 2014. "Bond Supply and Excess Bond Returns." *The Review of Financial Studies* 27 (3):663–713.

Greenwood, Robin M and Annette Vissing-Jorgensen. 2018. "The impact of pensions and insurance on global yield curves." Tech. rep., Harvard Business School Finance Working Paper.

Grinblatt, Mark and Bing Han. 2005. "Prospect theory, mental accounting, and momentum." *Journal of Financial Economics* 78 (2):311–339.

Grinblatt, Mark and Matti Keloharju. 2000. "The investment behavior and performance of various investor types: a study of Finland's unique data set." *Journal of Financial Economics* 55 (1):43–67.

Grinblatt, Mark and Tobias J. Moskowitz. 2004. "Predicting stock price movements from past returns: the role of consistency and tax-loss selling." *Journal of Financial Economics* 71 (3):541–579.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers. 1995. "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior." *The American Economic Review* 85 (5):1088–1105.

Gromb, Denis and Dimitri Vayanos. 2002. "Equilibrium and welfare in markets with financially constrained arbitrageurs." *Journal of Financial Economics* 66 (2):361–407.

Grossman, Sanford J. and Merton H. Miller. 1988. "Liquidity and Market Structure." *The Journal of Finance* 43 (3):617–633.

Grossman, Sanford J and Joseph E Stiglitz. 1980. "On the Impossibility of Informationally Efficient Markets." *American Economic Review* 70 (3):393–408.

Guibaud, Stéphane, Yves Nosbusch, and Dimitri Vayanos. 2013. "Bond market clienteles, the yield curve, and the optimal maturity structure of government debt." *The Review of Financial Studies* 26 (8):1914–1961.

Gulen, Huseyin and Michael Woeppel. 2022. "Price-path convexity, extrapolation, and short-horizon return predictability." Tech. rep.

Haddad, Valentin, Paul Huebner, and Erik Loualiche. 2022. "How Competitive is the Stock Market? Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing." Working paper.

Haddad, Valentin and Tyler Muir. 2021. "Do Intermediaries Matter for Aggregate Asset Prices?" *Journal of Finance* 76 (6):2719–2761.

Hartzmark, Samuel M and David H Solomon. 2022. "Predictable price pressure." Tech. rep.

He, Zhiguo, Bryan Kelly, and Asaf Manela. 2017. "Intermediary asset pricing: New evidence from many asset classes." *Journal of Financial Economics* 126 (1):1–35.

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

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

Hong, Harrison and Jeremy C Stein. 1999. "A unified theory of underreaction, momentum trading, and overreaction in asset markets." *The Journal of Finance* 54 (6):2143–2184.

Ippolito, Richard A. 1992. "Consumer reaction to measures of poor quality: Evidence from the mutual fund industry." *The Journal of Law and Economics* 35 (1):45–70.

Jansen, Kristy AE. 2021. "Long-term Investors, Demand Shifts, and Yields." Tech. rep.

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

———. 2001. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *The Journal of Finance* 56 (2):699–720.

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

Jiang, Zhengyang, Robert J Richmond, and Tony Zhang. 2022. "Understanding the Strength of the Dollar." Mimeo.

Johnson, Timothy C. 2002. "Rational Momentum Effects." *The Journal of Finance* 57 (2):585–608.

Kargar, Mahyar. 2021. "Heterogeneous intermediary asset pricing." *Journal of Financial Economics* 141 (2):505–532.

Kelly, Bryan T., Tobias J. Moskowitz, and Seth Pruitt. 2021. "Understanding momentum and reversal." *Journal of Financial Economics* 140 (3):726–743.

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

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

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

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

Kyle, Albert S. 1985. "Continuous Auctions and Insider Trading." *Econometrica* 53 (6):1315–1335. URL `http://www.jstor.org/stable/1913210`.

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

Lan, Chunhua, Fabio Moneta, and Russ Wermers. 2015. "Holding horizon: a new measure of active investment management." Tech. rep., American Finance Association Meetings.

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

Lochstoer, Lars A and Tyler Muir. 2022. "Volatility expectations and returns." *The Journal of Finance* 77 (2):1055–1096.

Long, J. Bradford De, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann. 1990. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *The Journal of Finance* 45 (2):379–395.

Lou, Dong. 2012. "A Flow-Based Explanation for Return Predictability." *The Review of Financial Studies* 25 (12):3457–3489.

Lou, Dong and Christopher Polk. 2021. "Comomentum: Inferring Arbitrage Activity from Return Correlations." *The Review of Financial Studies* 35 (7):3272–3302.

Luo, Jiang, Avanidhar Subrahmanyam, and Sheridan Titman. 2020. "Momentum and Reversals When Overconfident Investors Underestimate Their Competition." *The Review of Financial Studies* 34 (1):351–393.

Mainardi, Federico. 2023. "A Demand-Based Approach to Short-Selling." Tech. rep.

Malmendier, Ulrike and Stefan Nagel. 2011. "Depression Babies: Do Macroeconomic Experiences

Affect Risk Taking?*." *The Quarterly Journal of Economics* 126 (1):373–416.
———. 2016. " Learning from Inflation Experiences *." *The Quarterly Journal of Economics* 131 (1):53–87.
Martineau, Charles. 2021. "Rest in peace post-earnings announcement drift." *Critical Finance Review* .
McCarthy, Odhrain and Sebastian Hillenbrand. 2021. "Heterogeneous Investors and Stock Market Fluctuations." *Available at SSRN 3944887* .
Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf. 2012. "Currency momentum strategies." *Journal of Financial Economics* 106 (3):660–684.
Merton, Robert C. 1987. "A Simple Model of Capital Market Equilibrium with Incomplete Information." *The Journal of Finance* 42 (3):483–510.
Mitchell, Mark, Lasse Heje Pedersen, and Todd Pulvino. 2007. "Slow moving capital." *American Economic Review* 97 (2):215–220.
Moskowitz, Tobias J. and Mark Grinblatt. 1999. "Do Industries Explain Momentum?" *The Journal of Finance* 54 (4):1249–1290. URL `http://www.jstor.org/stable/798005`.
Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen. 2012. "Time series momentum." *Journal of Financial Economics* 104 (2):228–250.
Muravyev, Dmitriy, Neil D Pearson, and Joshua Matthew Pollet. 2022. "Anomalies and their short-sale costs." Tech. rep.
Nagel, Stefan and Zhengyang Xu. 2022. "Asset pricing with fading memory." *The Review of Financial Studies* 35 (5):2190–2245.
Noh, Don and Sangmin Oh. 2020. "Measuring institutional pressure for greenness: A demand system approach." Mimeo.
Novy-Marx, Robert. 2012. "Is momentum really momentum?" *Journal of Financial Economics* 103 (3):429–453.
———. 2015. "Fundamentally, momentum is fundamental momentum." Tech. rep., National Bureau of Economic Research.
Pastor, Lubos and Robert F. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy* 111 (3):642–685.
Pavlova, Anna and Taisiya Sikorskaya. 2022. "Benchmarking Intensity." *The Review of Financial Studies* .
Petajisto, Antti. 2009. "Why Do Demand Curves for Stocks Slope Down?" *Journal of Financial and Quantitative Analysis* 44 (5):1013–1044.
Rzeźnik, Aleksandra and Rüdiger Weber. 2022. "Money in the Right Hands: The Price Effects of Specialized Demand." Tech. rep.
Sadka, Ronnie. 2006. "Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk." *Journal of Financial Economics* 80 (2):309–349.
Shleifer, Andrei and Robert W. Vishny. 1997. "The Limits of Arbitrage." *The Journal of Finance* 52 (1):35–55.
Siriwardane, Emil, Aditya Sunderam, and Jonathan Wallen. 2021. "Segmented Arbitrage." Tech. rep., Working paper, HBS.
Sirri, Erik R. and Peter Tufano. 1998. "Costly Search and Mutual Fund Flows." *The Journal of Finance* 53 (5):1589–1622.
Tamoni, Andrea, Stanislav Sokolinski, and Yizhang Li. 2022. "Which Investors Drive Anomaly Returns and How?" Tech. rep.
van Binsbergen, Jules H., Martijn Boons, Christian C. Opp, and Andrea Tamoni. 2023. "Dynamic asset (mis)pricing: Build-up versus resolution anomalies." *Journal of Financial Economics* 147 (2):406–431.

Van Binsbergen, Jules H, Jungsuk Han, Hongxun Ruan, and Ran Xing. 2022. "A horizon based decomposition of mutual fund value added using transactions." .

van der Beck, Philippe. 2021. "Flow-driven ESG returns." Tech. rep., Swiss Finance Institute Research Paper.

———. 2022. "On the Estimation of Demand-Based Asset Pricing Models." Tech. rep., Swiss Finance Institute.

Van Wesep, Edward Dickersin and Brian Waters. 2021. "The Sky's the Limit: Bubbles and crashes when margin traders are all in." Tech. rep.

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

Vayanos, Dimitri and Paul Woolley. 2013. "An Institutional Theory of Momentum and Reversal." *The Review of Financial Studies* 26 (5):1087–1145.

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

A Equilibrium Momentum from Dynamic Trading

This appendix details formal derivations for Section 2. In particular, this section focuses on deriving the results of Proposition 1 in the presence of heterogeneous investors, as described in Section 2.4: Investors have demand curves

$$d_{it} = \underline{d}_i - \mathcal{E}_{\text{recent},i} \times (p_t - p_{t-1}) - \mathcal{E}_{\text{long-term},i} \times (p_{t-1} - p_{t-s}) \tag{IA.1}$$

$$D_t^{\phi} = \phi \times D_{t-1}^{\phi} + \epsilon_t^{\phi}, \tag{IA.2}$$

where lower-case and upper-case letters represent demand curves in logarithms and levels, respectively. Here i denotes an investor with elasticity $\mathcal{E}_{\text{recent},i}$ to recent and $\mathcal{E}_{\text{long-term},i}$ to longer-term price changes. Investor ϕ has persistent demand with demand shock ϵ_t^{ϕ} and persistence ϕ.

Next, define the aggregate, holdings-weighted recent and longer-term elasticities $\bar{\mathcal{E}}_{\text{recent},t}$ and $\bar{\mathcal{E}}_{\text{long-term},t}$:

$$\bar{\mathcal{E}}_{\text{recent},t} \equiv \int \exp(d_{it}) \mathcal{E}_{\text{recent},i} di \tag{IA.3}$$

$$\bar{\mathcal{E}}_{\text{long-term},t} \equiv \int \exp(d_{it}) \mathcal{E}_{\text{long-term},i} di. \tag{IA.4}$$

Based on fixed supply S, the market-clearing equation is:

$$\int D_{it} di = \int \exp(d_{it}) di = S - D_t^{\phi}. \tag{IA.5}$$

The model of Section 2.1 represents a special case of this setup with $I = 2$ investors: investor ST with $\underline{d}_{ST} = \underline{d}^{ST}$, $\mathcal{E}_{\text{recent},ST} = \mathcal{E}_{\text{recent}}$, $\mathcal{E}_{\text{long-term},ST} = 0$, and investor LT with $\underline{d}_{LT} = \underline{d}^{LT}$, $\mathcal{E}_{\text{recent},LT} = 0$, $\mathcal{E}_{\text{long-term},LT} = \mathcal{E}_{\text{long-term}}$. Section 2.2 further collapses these two investors into one, and Section 2.3 sets $\phi = 1$. Below, I provide derivations for the general case with heterogenous investors and $\phi \geq 0$, mirroring Section 2.4. All results in prior sections follow directly.

A.1 Derivations underlying the price impact of a recent demand shock

How much do prices move when a demand shock ϵ_t^{ϕ} arrives in the market? The answer depends on how strongly investors respond to recent price changes and, specifically, is proportional to the inverse of the aggregate elasticity to recent price changes, $\bar{\mathcal{E}}_{\text{recent},t}^{-1}$. I derive this result below.

Start with an exogenous shock to demand, ϵ_t^{ϕ}. Such a shock moves the residual supply of the asset, and consequently, the price of the asset changes. Differentiating both sides of the market-clearing equation (IA.5):

$$\frac{d}{d\epsilon_t^\phi}\int \exp(d_{it})di = -\int \exp(d_{it})\mathcal{E}_{\text{recent},i}\frac{dp_t}{d\epsilon_t^\phi}di = -\bar{\mathcal{E}}_{\text{recent},t}\frac{dp_t}{d\epsilon_t^\phi} = -1 = \frac{d}{d\epsilon_t^\phi}\left(S - D_t^\phi\right). \tag{IA.6}$$

The immediate price impact of a demand shock is:

$$\frac{dp_t}{d\epsilon_t^\phi} = \bar{\mathcal{E}}_{\text{recent},t}^{-1}. \tag{IA.7}$$

Define residual supply $\tilde{S}_t$ as $\tilde{S}_t \equiv S - D_t^\phi$. Then equation (11) follows: A one-unit residual supply shock moves prices by the inverse of the aggregate elasticity to recent price changes, $\bar{\mathcal{E}}_{\text{recent},t}^{-1}$.

A.2 Derivations underlying the long-term price impact

Now move forward one period. Is there a follow-on price impact to a demand shock from the previous period? Again start with an exogenous demand shock, ϵ_{t-1}^ϕ, but already occurring at time $t-1$, such that it moves prices at $t-1$. Based on the market-clearing equation (IA.5):

$$\frac{d}{d\epsilon_{t-1}^\phi}\int \exp(d_{it})di = -\frac{dD_t^\phi}{d\epsilon_{t-1}^\phi} \tag{IA.8}$$

$$-\int \exp(d_{it})\left(\mathcal{E}_{\text{recent},i}\frac{dp_t - dp_{t-1}}{d\epsilon_{t-1}^\phi} + \mathcal{E}_{\text{long-term},i}\frac{dp_{t-1}}{d\epsilon_{t-1}^\phi}\right)di = \phi\frac{dD_{t-1}^\phi}{d\epsilon_{t-1}^\phi} \tag{IA.9}$$

$$-\bar{\mathcal{E}}_{\text{recent},t}\frac{dp_t}{d\epsilon_{t-1}^\phi} - \left(\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}\right)\frac{dp_{t-1}}{d\epsilon_{t-1}^\phi} = \phi \tag{IA.10}$$

$$\frac{\bar{\mathcal{E}}_{\text{recent},t}\frac{dp_t}{d\epsilon_{t-1}^\phi} + \left(\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}\right)\frac{dp_{t-1}}{d\epsilon_{t-1}^\phi}}{\bar{\mathcal{E}}_{\text{recent},t-1}\frac{dp_{t-1}}{d\epsilon_{t-1}^\phi}} = \phi \tag{IA.11}$$

$$\frac{\bar{\mathcal{E}}_{\text{recent},t}\frac{dp_t}{d\epsilon_{t-1}^\phi} + \left(\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}\right)\frac{dp_{t-1}}{d\epsilon_{t-1}^\phi}}{\bar{\mathcal{E}}_{\text{recent},t}\frac{dp_{t-1}}{d\epsilon_{t-1}^\phi}} = \phi\frac{\bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}} \tag{IA.12}$$

$$\frac{\frac{dp_t}{d\epsilon_{t-1}^\phi}}{\frac{dp_{t-1}}{d\epsilon_{t-1}^\phi}} + \frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}}{\bar{\mathcal{E}}_{\text{recent},t}} = \phi\frac{\bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}}. \tag{IA.13}$$

Rearranging leads to the follow-on price impact of a past demand shock, as displayed in equations (16) and (17):

$$\frac{dp_t}{d\epsilon^{\phi}_{t-1}} = \left(\phi\frac{\bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}} - \frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}}{\bar{\mathcal{E}}_{\text{recent},t}}\right)\frac{dp_{t-1}}{d\epsilon^{\phi}_{t-1}} \tag{IA.14}$$

$$\Delta p_t + \Delta p_{t-1} = \left(\phi\frac{\bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}} - \frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}}{\bar{\mathcal{E}}_{\text{recent},t}}\right)\Delta p_{t-1} \tag{IA.15}$$

$$\Delta p_t = \left((\phi - 1)\frac{\bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}} - \frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t-1}}{\bar{\mathcal{E}}_{\text{recent},t}}\right)\Delta p_{t-1} \tag{IA.16}$$

$$\approx \left(\phi - 1 - \frac{\bar{\mathcal{E}}_{\text{long-term},t} - \bar{\mathcal{E}}_{\text{recent},t}}{\bar{\mathcal{E}}_{\text{recent},t}}\right)\Delta p_{t-1}. \tag{IA.17}$$

Equation (IA.15) uses the definitions $\Delta p_{t-1} \equiv \frac{dp_{t-1}}{d\epsilon^{\phi}_{t-1}}$ and $\Delta p_t \equiv \frac{dp_t}{d\epsilon^{\phi}_{t-1}} - \Delta p_{t-1}$ to denote the initial and follow-on price impacts of exogenous demand shocks from $t-1$. The approximation in (IA.17) replaces $\bar{\mathcal{E}}_{\text{recent},t-1}$ with $\bar{\mathcal{E}}_{\text{recent},t}$. It shuts down a second-order effect based on local time-series variation in aggregate elasticities to recent price changes. In my estimates, such variation is solely driven by composition effects in stock ownership. However, a stock's ownership distribution is strongly persistent over time, motivating this approximation.

B Identification Strategy

B.1 Moment Conditions

I estimate the model for each investor i using an instrumental variables approach. The identifying assumption is:

$$\mathbf{E}_i\left[\epsilon_{it}(n)|\mathbf{X}_t(n), \widehat{\Delta p}_{it}(n), \widehat{\Delta p}_{i,t-1}(n)\right] = 0. \tag{IA.18}$$

The resulting moment conditions are:

$$\mathbf{E}_i\left[\epsilon_{it}(n)\right] = 0, \forall i, \forall t \tag{IA.19}$$

$$\mathbf{E}_i\left[\epsilon_{it}(n)\mathbf{X}_t(n)\right] = \mathbf{0}, \forall i \tag{IA.20}$$

$$\mathbf{E}_i\left[\epsilon_{it}(n)\widehat{\Delta p}_{it}(n)\right] = 0, \forall i \tag{IA.21}$$

$$\mathbf{E}_i\left[\epsilon_{it}(n)\widehat{\Delta p}_{i,t-1}(n)\right] = 0, \forall i \tag{IA.22}$$

There are precisely as many moment conditions as parameters in the model.

B.2 Deriving flow-induced trading

I start by deriving the flow-induced trading instrument proposed by Lou (2012) by shutting off variation in equilibrium returns from equation (21) that is driven by endogenous sources.

$$\Delta p_t(n) = \log\left(\frac{\sum_j A_{jt} w_{jt}(n)}{\sum_j A_{j,t-1} w_{j,t-1}(n)}\right) \tag{IA.23}$$

$$\approx \log\left(\frac{\sum_j A_{jt} w_{j,t-1}(n)}{\sum_j A_{j,t-1} w_{j,t-1}(n)}\right) \tag{IA.24}$$

$$\approx \log\left(\frac{\sum_j A_{j,t-1}(1+f_{jt}) w_{j,t-1}(n)}{\sum_j A_{j,t-1} w_{j,t-1}(n)}\right) \tag{IA.25}$$

$$= \log\left(1 + \frac{\sum_j A_{j,t-1} w_{j,t-1}(n) f_{jt}}{\sum_j A_{j,t-1} w_{j,t-1}(n)}\right) \tag{IA.26}$$

$$\approx \frac{\sum_j A_{j,t-1} w_{j,t-1}(n) f_{jt}}{\sum_j A_{j,t-1} w_{j,t-1}(n)} \tag{IA.27}$$

$$= \sum_j o_{j,t-1}(n) f_{jt} \equiv FIT_t(n). \tag{IA.28}$$

Equation (IA.23) starts from the same market-clearing equation for equilibrium returns as equation (21). Current portfolio weights are correlated with demand shocks because they depend on market-clearing price changes. The first step toward the flow-induced trading instrument is replacing endogenous portfolio shares $w_{jt}(n)$ by past portfolio shares $w_{j,t-1}(n)$ in equation (IA.24). However, endogenous variation from prices does not only operates through portfolio weights but also wealth effects, which are next excluded by replacing institutions' AUM A_{jt} by past their past AUM $A_{j,t-1}$ in equation (IA.25). Equation (IA.27) applies the well-known approximation $\log(1+x) \approx x$, for x close to zero. Finally, equation (IA.28) introduces the instrument, flow-induced trading ($FIT_t(n)$): The past-ownership weighted average of fund flows. This is a commonly used instrument for returns in the literature (Lou, 2012).

B.3 The identification of demand elasticities

Are $\mathcal{E}_{\text{recent},i}$ and $\mathcal{E}_{\text{long-term},i}$ the elasticities of investor i's demand to recent and longer-term price changes?

Denote by $q_{it}(n)$ the log number of shares investor i demands of asset n at time t:

$$q_{it}(n) = \log\left(A_{it} w_{it}(n)\right) - p_t(n) \tag{IA.29}$$

$$= \log\left(A_{it} w_{it}(n)\right) - \sum_{s \geq 0} \Delta p_{t-s}(n). \tag{IA.30}$$

The demand elasticity to the recent price changes is:

$$-\frac{dq_{it}(n)}{d\Delta p_t(n)} = 1 - \frac{d}{d\Delta p_t(n)} \log\left(A_{it} w_{it}(n)\right) \tag{IA.31}$$

$$= 1 - \frac{1}{A_{it} w_{it}(n)} \left(A_{it} \underbrace{\frac{dw_{it}(n)}{d\Delta p_t(n)}}_{= w_{it}(n)(1-\mathcal{E}_{\text{recent},i})(1-w_{it}(n))} + w_{it}(n) \underbrace{\frac{dA_{it}}{d\Delta p_t(n)}}_{= A_{i,t-1} w_{ik,t-1}} \right) \tag{IA.32}$$

$$= 1 - (1 - \mathcal{E}_{\text{recent},i})(1 - \underbrace{w_{it}(n)}_{\approx 0}) - \frac{A_{i,t-1}}{A_{it}} \underbrace{w_{i,t-1}(n)}_{\approx 0} \tag{IA.33}$$

$$\approx \mathcal{E}_{\text{recent},i}. \tag{IA.34}$$

Similar to Koijen and Yogo (2019), the elasticity implied by the demand equation of investor i is not exactly but approximately equal to $\mathcal{E}_{\text{recent},i}$ for current and past portfolio weights close to zero, which is the empirically relevant case. While the factor $1 - w_{it}(n)$ on $1 - \mathcal{E}_{\text{recent},i}$ comes from substitution through the outside asset as in their demand system, the term $\frac{A_{i,t-1}}{A_{it}} w_{i,t-1}(n)$ is unique to this setup: it captures a wealth effect from the dynamics of an institution's assets and makes demand less elastic. Van Wesep and Waters (2021) argue that such wealth effects can lead to upward-sloping demand curves.

The demand elasticity to longer-term price changes is:

$$-\frac{dq_{it}(n)}{d\Delta p_{t-1}(n)} = 1 - \frac{d}{d\Delta p_{t-1}(n)} \log\left(A_{it} w_{it}(n)\right) \tag{IA.35}$$

$$= 1 - (1 - \mathcal{E}_{\text{long-term},i})(1 - \underbrace{w_{it}(n)}_{\approx 0}) - \frac{A_{i,t-2}}{A_{i,t-1}} \underbrace{w_{ik,t-2}}_{\approx 0} \tag{IA.36}$$

$$\approx \mathcal{E}_{\text{long-term},i}. \tag{IA.37}$$

A similar derivation as for recent returns shows that the demand elasticity to longer-term price changes implied by the model is approximately $\mathcal{E}_{\text{long-term},i}$. Recall that the interpretation of this longer-term demand elasticity is by how many percent an investor cumulatively adjusts their portfolio today in response to a one percent price change in the past.

C Appendix Tables

Table IA.1. Fund flow persistence and flow-performance relationship

	Quarterly Fund Flow f_{it}				
	(1)	(2)	(3)	(4)	(5)
Lagged Fund Flow $f_{i,t-1}$	0.222***	0.219***	0.218***	0.120**	0.127***
	(0.037)	(0.037)	(0.037)	(0.039)	(0.037)
Lagged Fund Flow $f_{i,t-2}$	0.135***	0.137***	0.136***	0.065**	0.072**
	(0.026)	(0.026)	(0.026)	(0.024)	(0.023)
Lagged Fund Flow $f_{i,t-3}$	0.089***	0.091***	0.090***	0.045***	0.052***
	(0.021)	(0.021)	(0.021)	(0.013)	(0.013)
Lagged Fund Flow $f_{i,t-4}$	0.059**	0.059**	0.059**	0.026*	0.032**
	(0.019)	(0.020)	(0.020)	(0.012)	(0.012)
Lagged Fund Return $\Delta p_{i,t-1}$	0.035*	0.150***	0.157***	0.164***	0.176***
	(0.016)	(0.027)	(0.027)	(0.035)	(0.030)
Lagged Fund Return $\Delta p_{i,t-2}$	0.013	0.045	0.053*	0.078***	0.092***
	(0.014)	(0.026)	(0.027)	(0.021)	(0.021)
Lagged Fund Return $\Delta p_{i,t-3}$	-0.002	0.011	0.020	0.049*	0.064***
	(0.013)	(0.020)	(0.020)	(0.020)	(0.018)
Lagged Fund Return $\Delta p_{i,t-4}$	0.008	-0.013	-0.004	0.035*	0.047**
	(0.015)	(0.021)	(0.021)	(0.016)	(0.016)
Date Fixed Effects		Yes	Yes	Yes	Yes
Size Decile Fixed Effects			Yes		Yes
Fund Fixed Effects				Yes	Yes
N	203,222	203,222	203,222	203,222	203,222
R^2	0.158	0.173	0.179	0.257	0.281

Table IA.1 reports coefficients from a panel regression of quarterly fund flows f_{it} on past fund flows $f_{i,t-s}$ and past fund returns $\Delta p_{i,t-s}$, for s between 1 and 4 quarters. Column 2 adds date-fixed effects. Column 3 adds size-decile fixed effects: Funds are sorted into deciles based on funds' past quarter's fund size, i.e. its total net assets. Column 4 uses date-fixed effects and fund-fixed effects. Column 5 combines all three types of fixed effects. The sample period is 1999-2020. Standard errors are 2-way clustered by date and fund for all columns.

Table IA.2.
Robustness of momentum returns based on the term structure of elasticities

	Lo-Hi η of Value-Weighted Momentum Returns		
	Average	Fama-French 3 α	Carhart 4 α
(1) Baseline Specification	6.82**	7.64**	7.03*
(2) Momentum Deciles	12.73**	13.23**	12.64**
(3) Elasticity Term-Structure η Quintiles	6.14	8.37*	6.14*
(4) Long-only Portfolio Sorts	9.96**	1.99*	2.71***
(5) Portfolio Sorts with Size Controls	3.73*	4.05*	3.67
(6) Absolute Elasticity Differences	6.79**	7.41**	6.67*
(7) BE-based Instrument	6.92**	6.57**	6.43*

Table IA.2 reports the difference of value-weighted momentum returns in stocks with a steeply decreasing term structure of elasticities, i.e. stocks with η lower than the median, versus in stocks with a flatter term structure. Column 1 reports average returns, while columns 2 and 3 show the anomaly α with respect to the Fama and French (1993) and Carhart (1997) factor models. Specification (1) is the baseline specification from column 4 of table 5. The baseline specification uses the top tercile of winners during the formation period for the long leg, and the bottom tercile for the short leg. Specification (2) instead defines the long and short legs at the top and bottom deciles. While the baseline specification sorts stock based on whether the term structure of elasticities η is above or below the median, specification (3) contrasts the performance of momentum across η quintiles. Specification (4) implements a long-only version of a strategy that goes long momentum in low η momentum stocks and short momentum in high η reversal stocks. Specification (5) non-linearly controls for size by initially sorting stocks by size quintiles and subsequently averaging across them. Specification (6) considers the absolute instead of the relative difference between aggregate real-time and past elasticities, i.e. instead of sorting by η as defined in equation (30), it initially sorts by the difference of the elasticities in equations (28) and (29). Finally, specification (7) uses an alternative instrument that uses book-equity-based pseudo holdings in the construction of the instrument. The sample period is from 1999 to 2020. Standard errors are estimated using Newey-West with 12 lags. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively.

D Appendix Figures

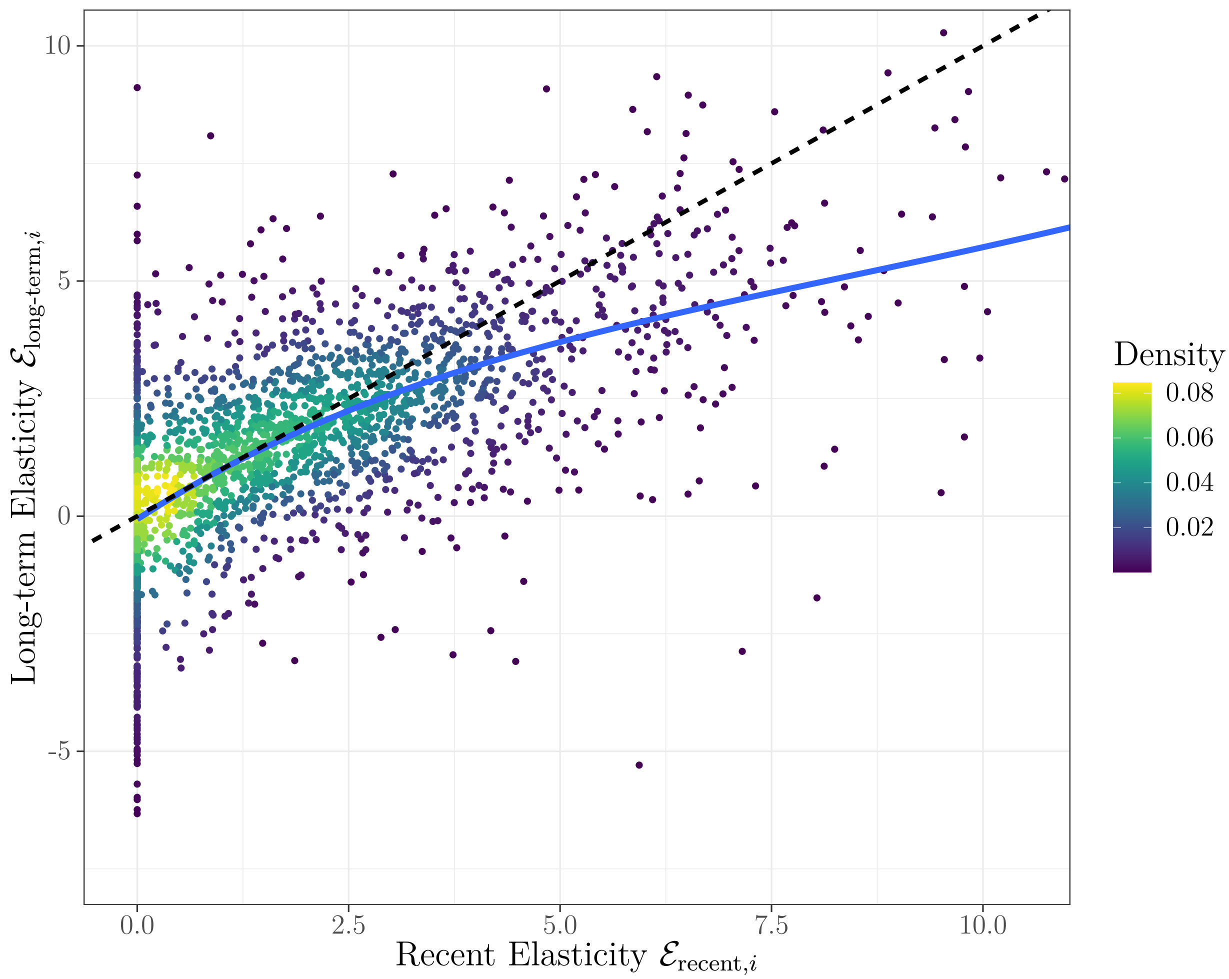


Figure IA.1. Estimates for elasticities $\mathcal{E}_{\text{recent},i}$ and $\mathcal{E}_{\text{long-term},i}$ among institutions with long data histories

Figure IA.1 shows a scatterplot of elasticity estimates for elasticities to price changes over the past quarter, $\mathcal{E}_{\text{recent},i}$, on the x-axis, and variation over the three preceding quarters, $\mathcal{E}_{\text{long-term},i}$, on the y-axis. Compared to Figure 2, it filters to institutions that appear in the data for at least 30 quarters throughout the sample period between 1999 and 2020. Each dot represents one institutional investor in the sample. The solid blue line is a fitted trend line based on cubic regression, and the black dashed line represents flat term structures of elasticities, $\mathcal{E}_{\text{long-term},i} = \mathcal{E}_{\text{recent},i}$. Dots below the dashed line represent downward-sloping term structures of elasticities. The estimation equation is equation (19).

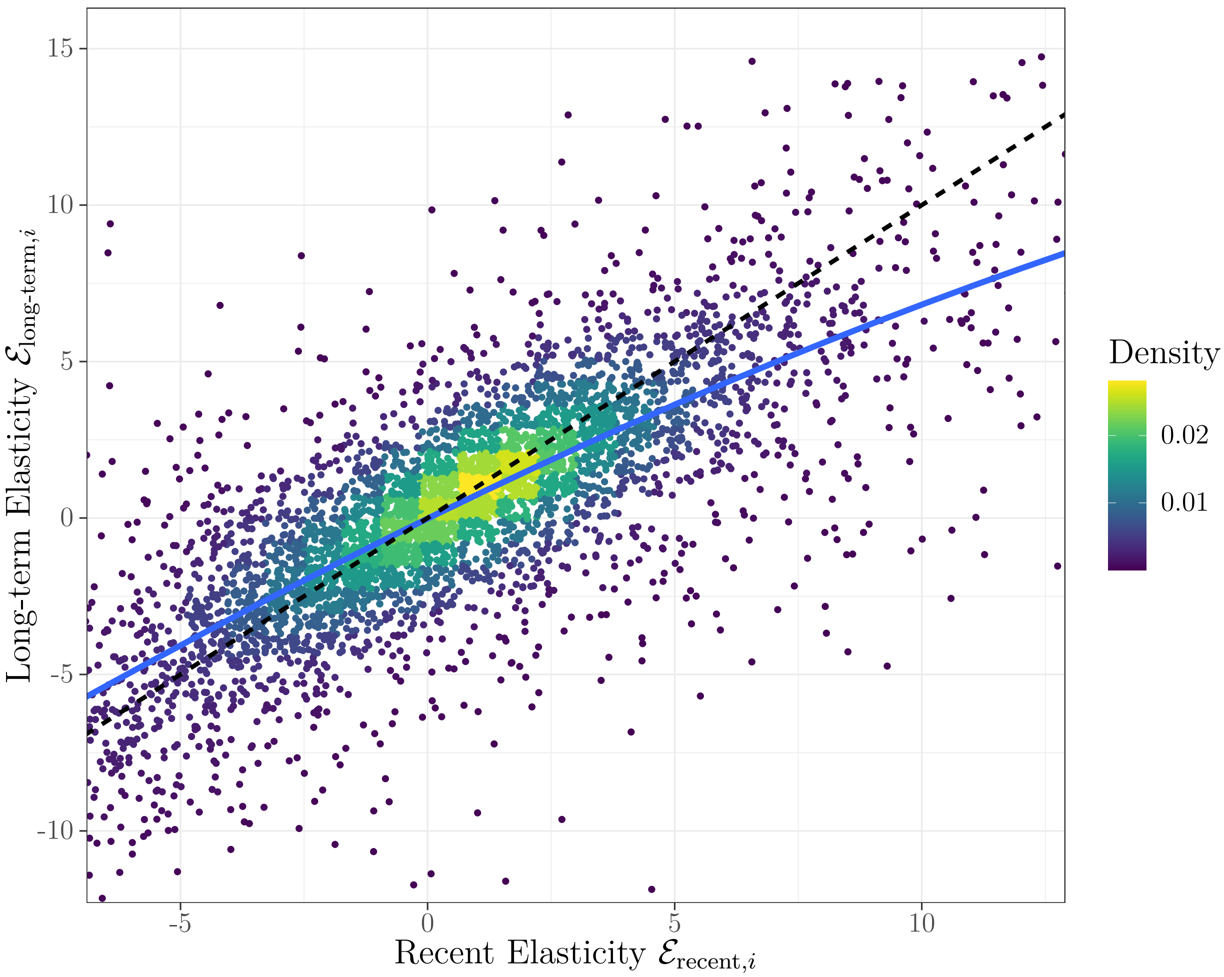


Figure IA.2. Unconstrained estimates for elasticities $\mathcal{E}_{\text{recent},i}$ and $\mathcal{E}_{\text{long-term},i}$ controlling for the past price level
Figure IA.2 shows a scatterplot of elasticity estimates for elasticities to price changes over the past quarter, $\mathcal{E}_{\text{recent},i}$, on the x-axis, and variation over the three preceding quarters, $\mathcal{E}_{\text{long-term},i}$, on the y-axis. Compared to Figure 2, it allows for (*i*) negative elasticities to price changes over the previous quarter and (*ii*) controls for the market-to-book ratio one year ago, instrumented by a Koijen and Yogo (2019) type of instrument. Each dot represents one institutional investor in the sample. The solid blue line is a fitted trend line based on cubic regression, and the black dashed line represents flat term structures of elasticities, $\mathcal{E}_{\text{long-term},i} = \mathcal{E}_{\text{recent},i}$. Dots below the dashed line represent downward-sloping term structures of elasticities. The estimation equation is:

$$\log \frac{w_{it}(n)}{w_{it}(0)} = (1-\mathcal{E}_{\text{recent},i})\ \Delta p_t(n) + (1-\mathcal{E}_{\text{long-term},i})\ \left(\sum_{s=1}^{3} \Delta p_{t-s}(n)\right) + (1-\mathcal{E}_{\text{KY},i}))\ \left(p_{t-s}(n) - \text{be}_{t-s}(n)\right) + \underline{d}_{0it} + \underline{d}_{1i}' X_t(n) + \epsilon_{it}(n). \quad \text{(IA.38)}$$

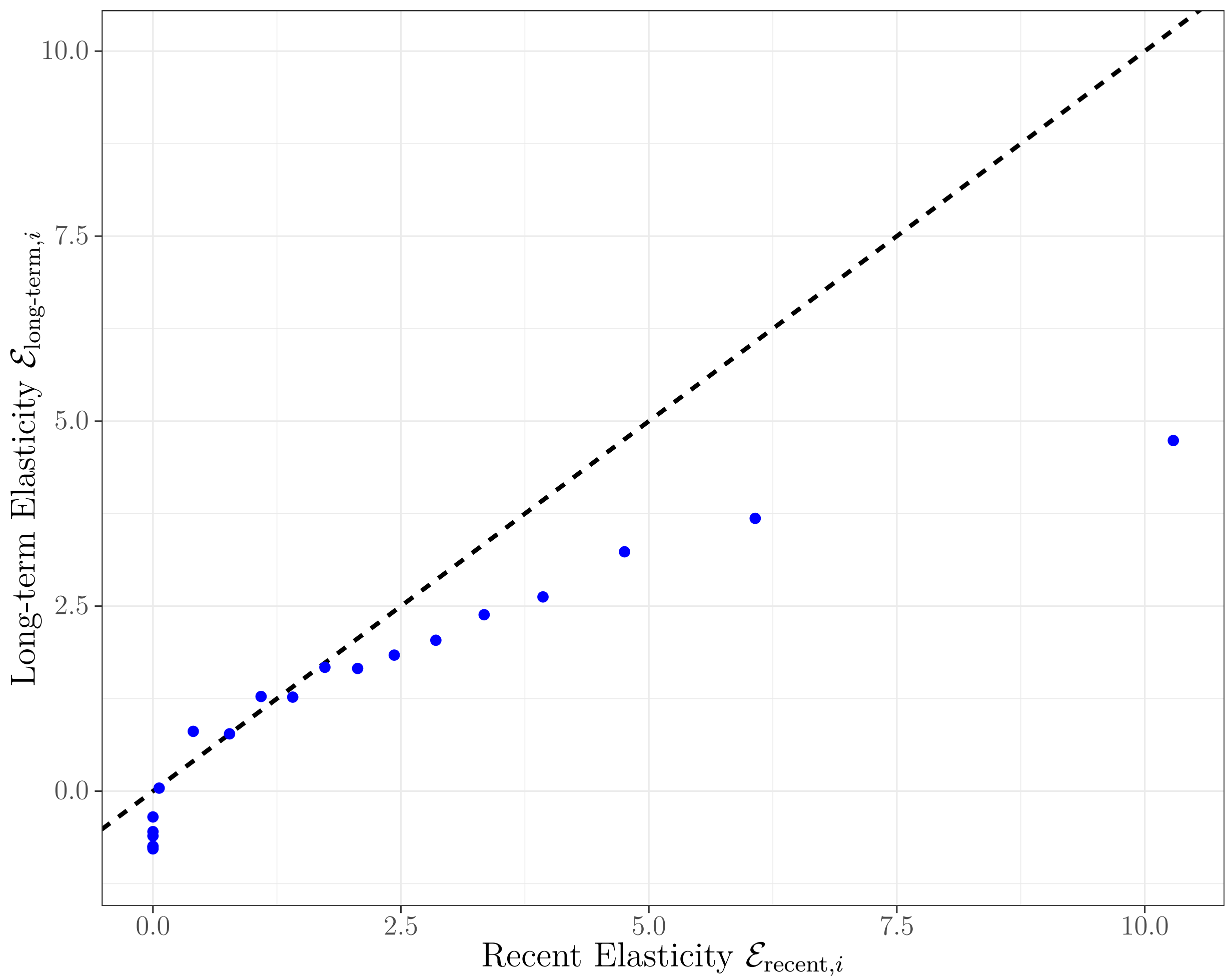


Figure IA.3. Grouped estimates for elasticities $\mathcal{E}_{\text{recent},i}$ and $\mathcal{E}_{\text{long-term},i}$
Figure IA.3 shows a binned scatterplot of elasticity estimates for elasticities to price changes over the past quarter, $\mathcal{E}_{\text{recent},i}$, on the x-axis, and variation over the three preceding quarters, $\mathcal{E}_{\text{long-term},i}$, on the y-axis. That is, it shows a binned version of Figure 2. Each dot represents one of twenty bins of institutional investors in the sample. The black dashed line represents flat term structures of elasticities, $\mathcal{E}_{\text{long-term},i} = \mathcal{E}_{\text{recent},i}$. Dots below the dashed line represent downward-sloping term structures of elasticities. The estimation equation is equation (19).