Expectations and Inelastic Markets*

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Abstract

We study the role of expectations in identifying demand elasticities, and in understanding the sources of inelastic markets. Empirical estimates of price multipliers need not identify demand elasticities: demand elasticities measure how responsive holdings are to off-equilibrium changes in prices, whereas price multipliers are equilibrium objects. As such, price multipliers may confound movements along the demand curve with shifts in its intercept. Departing from full information rational expectations weakens the conditions required for identification: under incomplete information, shocks outside investors' information sets no longer shift the intercept of their demand curves. More broadly, demand elasticities themselves depend on the information environment and on how investors form expectations. For example, learning from prices makes the submitted demand curve more inelastic, providing a mechanism that jointly explains excess volatility and inelastic markets.

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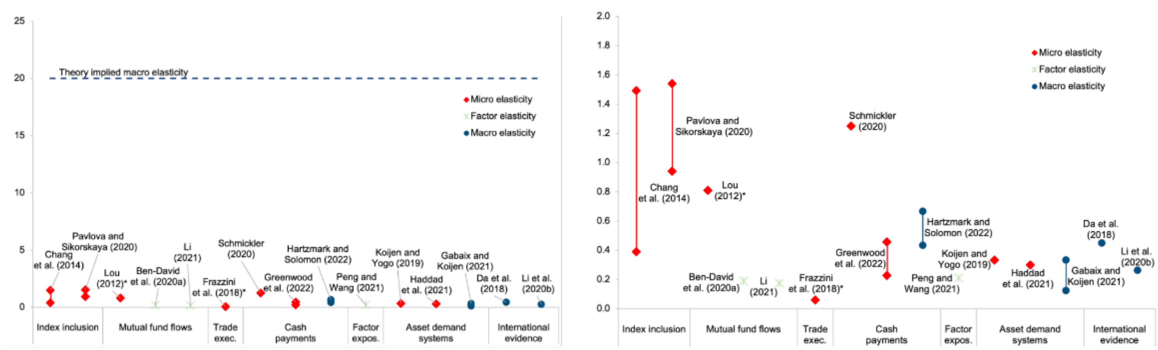
1 Introduction

Why are stock prices excessively volatile, while investors' holdings are fairly stable? A growing body of work suggests this may be due to markets being inelastic (Shleifer 1986, Gabaix and Koijen 2023): since investors' holdings don't respond strongly to shocks, prices must adjust substantially in order to restore market clearing. However, the reason why markets are inelastic still remains an open question: as shown in Figure 1, empirical estimates of demand elasticities appear to be too low relative to their theory-implied counterparts.[1]

Figure 1: Theory-implied macro elasticities and empirical estimates



Source: Gabaix and Koijen (2022)

This raises two questions. First, to what extent might this gap be due to a discrepancy between the theory and empirical objects being compared? Second, once identification is taken into account, what contributes to markets being inelastic?

This paper studies the role of beliefs in answering both questions. First, we show that once we depart from the full information rational expectations benchmark, the conditions under which empirical estimates identify theory-implied demand elasticities become less restrictive. Second, demand elasticities themselves depend on the informa-

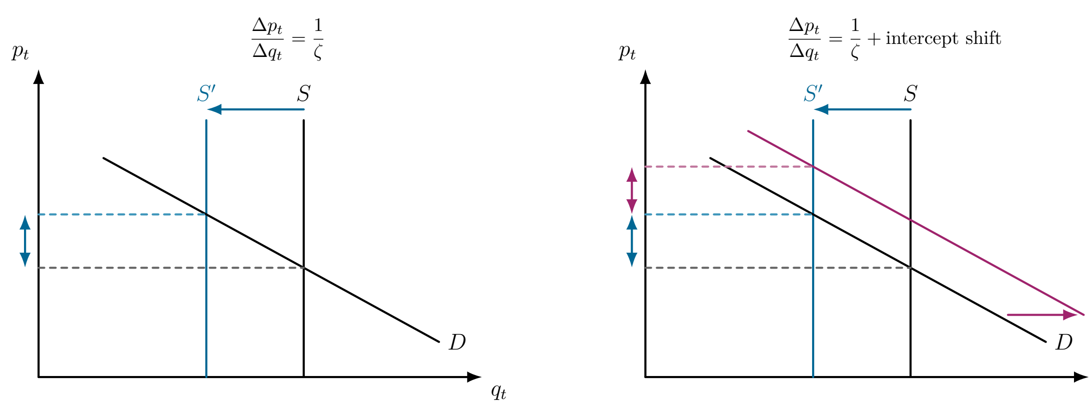
[1]The estimates in Figure 1 come from several empirical settings. Some studies exploit shocks related to index inclusion, including Chang et al. (2015) and Pavlova and Sikorskaya (2023). Others use variation in mutual fund flows (Lou 2012, Ben-David et al. 2022, Li 2022), trade execution (Frazzini et al. 2018), cash distributions (Schmickler 2020, Greenwood et al. 2023, Hartzmark and Solomon 2025), or factor exposures (Peng and Wang 2021). A separate group estimates asset demand systems directly (Koijen and Yogo 2019, Haddad et al. 2021, Gabaix and Koijen 2023), while Da et al. (2018) and Li et al. (2021) provide international evidence.

tion environment and on how investors form expectations. For example, learning from prices makes the submitted demand curve more inelastic, providing a mechanism that jointly explains excess volatility and inelastic markets.

We start by asking whether the gap between theory and empirical estimates of demand elasticities reflects a discrepancy between the objects being compared. Empirical estimates of demand elasticities are typically inferred from the equilibrium response of prices to exogenous supply shocks, which we refer to as the price multiplier. As shown in the left panel of Figure 2, such shocks trace out the demand curve, and the demand elasticity can be inferred from the inverse of the price multiplier.

However, in the context of financial markets, finding shocks that only shift supply while leaving the demand curve unchanged can be particularly challenging. This is because the demand for risky assets is forward-looking. Investors care not only about today's price, but also about future resale values. If the supply shock is observed and persistent (such as for index inclusion events), it also changes investors' expectations of future resale values, altering their willingness to hold the asset at any given price. In other words, such shocks shift the demand curve as well, as shown in the right panel of Figure 2. This poses a challenge for identification, as price multipliers now confound movements along the demand curve with shifts in the intercept of the demand curve.

Figure 2: Identifying Demand Elasticities



(a) Shock identifies the demand elasticity. (b) Shock does not identify the demand elasticity.

How investors form expectations of future resale values is central to this identification challenge. Despite this, prior work has largely maintained the assumption of full information rational expectations. Under this benchmark, identification is only possible when supply shocks are completely transitory. Any persistent supply shock automatically changes investors' expectations of future resale values, shifting the demand curve itself. The necessity of completely transitory shocks is a stringent requirement that few empirical settings are likely to satisfy.

We show how relaxing the assumption of full information rational expectations weakens the requirements for identification, and changes what determines demand elasticities themselves.

We start by relaxing the assumption of full information. Investors no longer perfectly observe all current and past fundamentals. Instead, they receive noisy signals, and some shocks may be unobservable. The relevant question for identification is no longer whether a flow shock is persistent, but whether it is part of investors' information set. Shocks that investors do not observe cannot directly affect their expectations of future resale values. As a result, they do not shift the intercept of the demand curve, and their inverse multiplier identifies the demand elasticity regardless of the persistence of the shock.

These identification results allow us to reinterpret existing empirical estimates of demand elasticities. Public events, such as index inclusions, are closer to observed shocks. These shocks may shift demand directly, so their multipliers confound movements along the demand curve with shifts in its intercept. By contrast, designs based on flow-induced trading or mutual fund flows exploit shocks that may be closer to unobserved. The inverse multipliers estimated in these settings are therefore more likely to recover the relevant demand elasticity.

To understand what determines demand elasticities themselves, we then distinguish between two canonical concepts from the information economics literature: the competitive equilibrium and the rational expectations equilibrium. Under the competitive equilibrium, investors form expectations using only exogenous signals. Prices then only have their traditional role as a measure of scarcity: when prices increase, the asset becomes more expensive, and investors want to hold less of it. Instead, under the rational expectations equilibrium, investors also learn information from prices. Prices therefore also acquire an informational role: higher prices are associated with higher expected future resale values, leading investors to want to hold more of the asset. Learning from prices therefore changes the slope of the submitted demand curve itself, making demand more inelastic. A simple calibration suggests that this mechanism may be quantitatively important, potentially reducing the gap between theoretical and empirical demand elasticities by roughly an order of magnitude.

Finally, we relax the assumption of rational expectations. The distinction between the competitive equilibrium and the rational expectations equilibrium naturally extends to biased beliefs. We therefore compare two corresponding forms of mislearning: mislearning from exogenous fundamentals, which mirrors the competitive equilibrium, and mislearning from prices, which mirrors the rational expectations equilibrium. We show that these two forms of mislearning have different implications for inelastic markets. Mislearning from exogenous fundamentals shifts the intercept of investors' demand curves, but leaves their slope—and therefore the demand elasticity—unchanged. By contrast, mislearning from prices changes both the intercept and the slope of demand, and can therefore generate both excess volatility and inelastic markets. These results highlight how jointly studying beliefs, prices, and quantities can help identify the mechanisms driving fluctuations in asset prices.

This paper contributes to three literatures. First, it contributes to the debate on the drivers of inelastic markets (Gabaix and Koijen 2023), and draws a distinction between components of the price multiplier arising from movements along the demand curve and shifts in its intercept (Bastianello and Fontanier 2025, He et al. 2026, van Binsbergen et al. 2026).[2] We show how investors' information sets determine whether the price multiplier identifies the demand elasticity. Consistent with prior work, we show how under full information rational expectations, identification requires shocks to be completely

[2] While we mostly focus on macro-elasticities, recent work has also studied challenges in identifying micro-elasticities as well Haddad et al. 2025, Fuchs et al. 2023, Fuchs et al. 2025.

transitory and not affect investors' expectations of future resale values. Instead, under incomplete information, identification can be achieved even with shocks that are persistent, and with shocks that affect expected future resale values, as long as they only do so via their effect on equilibrium prices. Second, the paper connects the demand-based asset pricing literature to a long-standing body of work in information economics (Grossman 1976, Grossman and Stiglitz 1976, Diamond and Verrecchia 1981).[3] We show that the slope of the demand curve differs under a competitive equilibrium (with no learning from prices) and under a rational expectations equilibrium (with learning from prices). Third, the paper studies how biased beliefs may contribute to inelastic markets, and how data on holdings may inform models of beliefs (Giglio et al. 2021, Egan et al. 2022, Bastianello and Fontanier 2025, Bastianello and Fontanier 2026, Chaudhry 2025, Graves 2025, Graves 2026). While mislearning from fundamentals and mislearning from prices can both amplify price multipliers and contribute to excess volatility, they have very different implications for demand elasticities

The paper proceeds as follows. Section 2 distinguishes between demand elasticities and price multipliers. Section 3 revisits the full information rational expectations benchmark. Section 4 introduces incomplete information, studies how the mapping between price multipliers and demand elasticities depends on investors' information sets, and examines the role of learning from prices. Section 5 studies how biased beliefs contribute to inelastic markets, contrasting mislearning from exogenous fundamentals with mislearning from prices. Section 6 concludes.

2 Demand Elasticity and Price Multiplier

We start from a simple setting that introduces demand elasticities and price multipliers, and highlights the role of expectations in understanding the evidence on inelastic markets.

Assume that investors have CARA utility over next period wealth, and that they

[3]See Veldkamp 2011 for a review.

solve a portfolio choice problem between a risky and a risk-free asset. The risk-free asset is in perfectly elastic supply, and we normalize its price and rate of return to 1. The risky asset is also in zero-net supply, and it pays off a dividend D_t per share in each period t. We let P_t be the price of the risky asset, and Q_t be the number of shares held by a representative investor. Standard optimization then leads to the following demand function:

$$Q_t = \frac{\pi_t}{A\mathbb{V}P_t} \implies q_t = -p_t + \log(\pi_t) - \log(A\mathbb{V}) \tag{1}$$

where $\pi_t \equiv \frac{\mathbb{E}_t[D_{t+1}+P_{t+1}]-P_t}{P_t}$ captures investors' expected return at time t, $\mathbb{V}$ is the variance of returns (which we assume for simplicity to be constant over time and across individuals), and A is the coefficient of absolute risk aversion. Lower case letters represent logs of the corresponding upper case variable.

Demand Elasticity. The demand elasticity then captures how investors adjust their holdings in response to an *off-equilibrium* change in prices (holding all other exogenous quantities that are part of investors' information set fixed). Taking the partial derivative of investors' demand function in (1), and assuming that $A\mathbb{V}$ is constant, we can write the demand elasticity as:[4]

$$-\frac{\partial q_t}{\partial p_t} = 1 - \left(\frac{\partial q_t}{\partial \pi_t}\right) \times \left(\frac{\partial \pi_t}{\partial p_t}\right) \tag{3}$$

The first term captures the direct effect of prices on quantities: when the asset is more expensive, investors want to hold less of it. The second term captures how changes in prices may also mechanically change investors' expected returns. This latter component clearly depends on how investors form expectations.

[4] If we relax the assumption that return variance is constant, we can write the demand elasticity as:

$$-\frac{\partial q_{it}}{\partial p_t} = 1 - \left(\frac{\partial q_{it}}{\partial \pi_{it}}\right) \times \left(\frac{\partial \pi_{it}}{\partial p_t}\right) + \left(\frac{\partial q_{it}}{\partial \mathbb{V}}\right) \times \left(\frac{\partial \mathbb{V}}{\partial p_t}\right) \tag{2}$$

If return variance rises when prices fall, the third term in this expression contributes to markets being more inelastic as well (He et al. 2026). We abstract from this channel in our analysis.

Price Multiplier. Turning to empirical estimates of demand elasticities, these are generally obtained by taking the inverse of the price multiplier with respect to exogenous supply shifters. Importantly, price multipliers are *equilibrium* objects. To derive them, let the net supply of the risky asset be $-f_t$ (so that a positive f_t corresponds to a reduction in net supply, or equivalently a positive demand shock). Imposing market clearing yields:

$$p_t = \log(\pi_t) - \log(A\mathbb{V}) + f_t \tag{4}$$

Taking the derivative with respect to f_t gives us the following price multiplier:

$$\frac{dp_t}{df_t} = \frac{1}{\pi_t}\frac{d\pi_t}{df_t} + 1 = \frac{1}{\pi_t}\left(\frac{\partial \pi_t}{\partial p_t}\frac{dp_t}{df_t} + \frac{\partial \pi_t}{\partial f_t}\right) + 1 \implies \frac{dp_t}{df_t} = \frac{1 + \left(\frac{\partial q_t}{\partial \pi_t}\right)\left(\frac{\partial \pi_t}{\partial f_t}\right)}{1 - \left(\frac{\partial q_t}{\partial \pi_t}\right)\left(\frac{\partial \pi_t}{\partial p_t}\right)} \tag{5}$$

where the second equality shows how expected returns may change both through the influence of the shock on prices ($\frac{\partial \pi_t}{\partial p_t}\frac{\partial p_t}{\partial f_t}$), and through a direct effect ($\frac{\partial \pi_t}{\partial f_t}$). The third equality on the right hand side simply solves for the price multiplier (and uses $\frac{\partial q_t}{\partial \pi_t} = \frac{1}{\pi_t}$).

This paper. In what follows we are interested in answering two questions. First, when do empirically estimated inverse multipliers identify theoretical demand elasticities? Second, conditional on demand elasticities being low, what contributes to markets being inelastic? We show that understanding the role of belief formation is key in answering both questions.

2.1 Identifying Demand Elasticities from Price Multipliers

We start by understanding how belief formation plays an important role in assessing when inverse multipliers identify demand elasticities. Comparing (5) and (3), the inverse price multiplier identifies the demand elasticity if:

$$\frac{\partial \pi_t}{\partial f_t} = 0 \tag{6}$$

In other words, the inverse multiplier identifies the demand elasticity only when the shock does not *directly* impact investors' return expectations, holding prices fixed.

Whether this condition is satisfied depends on investors' information sets and, more generally, on how they form beliefs. Prior work has evaluated this condition under the assumption of full information rational expectations. This paper re-evaluates this condition when we relax both the assumption of full information and the assumption of rational expectations. For example, under incomplete information, some shocks may be unobserved by investors. Because these shocks are outside investors' information sets, they cannot *directly* affect expected returns. Consequently, condition (6) can hold even when it would fail under full information, substantially weakening the conditions required for identification.

2.2 The Role of Beliefs in Contributing to Inelastic Markets

Turning to the drivers of inelastic markets, the decomposition in (3) highlights how demand elasticities may be low either because the pass-through from beliefs to holdings is low ($\partial q_t/\partial \pi_t$), or because expected returns are not very responsive to changes in prices ($\partial \pi_t/\partial p_t$) (Gabaix and Koijen 2023, Davis et al. 2025).[5,6] Appendix B shows that, for the first channel to play a quantitatively meaningful role, we need to consider demand specifications that depart from CARA utility. We instead focus on the second channel, and study how belief formation shapes the responsiveness of expected returns to prices. As we show below, this channel can be quantitatively important for understanding the evidence on inelastic markets.

[5]In the limit where investors' expected returns are constant, holdings are also constant. Empirically, Nagel and Xu (2023) show that investors' expected returns are fairly stable over time, meaning that this second channel may be meaningful. More generally, Greenwood and Shleifer (2014) find evidence of pro-cyclical expected returns, while Bastianello (2022), Dahlquist and Ibert (2023), Thesmar and Verner (2026) find evidence of counter-cyclical expected returns among more sophisticated market participants, such as asset managers and equity analysts.

[6]Another way to assess the empirical relevance of this channel would be to perform a thought experiment similar to Davis (2025), but focusing on the sensitivity of expected returns to prices rather than the pass-through from beliefs to holdings. While some predictors used in quantitative strategies depend on prices (e.g., valuation ratios or momentum), others do not, and even price-based predictors may generate limited variation in expected returns. As a result, expected returns may respond weakly to changes in prices, contributing to inelastic demand.

To understand what determines the semi-elasticity of expected returns with respect to prices, we linearize expected returns around the steady state, to obtain the following expression (derived in Appendix A.1):

$$1 + \pi_{it} \approx (1 + \delta) - (1 + \delta)p_t + (\mathbb{E}_t[\delta d_{t+1} + p_{t+1}]) \tag{7}$$

where δ denotes the steady-state dividend-price ratio. The first term on the right hand side of (7) captures the average expected return, the second term captures how expected returns mechanically decrease as the asset becomes more expensive, and the third term captures how expected returns are increasing in investors' expectations of future payoffs.

We can then write the semi-elasticity of expected returns to changes in prices, while holding all other determinants of expected returns fixed, as:

$$\frac{\partial \pi_{it}}{\partial p_t} = -(1 + \delta) + \frac{\partial \mathbb{E}_t[\delta d_{t+1} + p_{t+1}]}{\partial p_t} \tag{8}$$

Equation (8) shows that prices affect expected returns through two channels. First, a higher current price mechanically lowers expected returns because the asset becomes more expensive. Second, if prices affect beliefs about future payoffs, for example due to learning from prices, expected returns rise. This second channel depends entirely on how investors form expectations. While the contribution of the first component in (8) to low demand elasticities is limited (as investors' average expected returns are in the right ball-park), the second component can play a quantitatively meaningful role, as further illustrated by the following calibration.

2.2.1 Calibration

To illustrate the relevance of the second component in (8) for demand elasticities, we consider two calibrations that make different assumptions, with and without learning from prices.

The theory implied estimate of the macro elasticity in Figure 1 is obtained by assuming that investors don't learn from prices, and therefore don't mechanically revise their expectations of future payoffs in response to price changes. Substituting (8) into (3), using $\frac{\partial q_t}{\partial \pi_t} = \frac{1}{\pi_t}$, and setting $\frac{\partial \mathbb{E}_t[\delta d_{t+1}+p_{t+1}]}{\partial p_t} = 0$, $\delta = 3.7\%$ and $\pi = 4.4\%$, yields:

$$-\frac{\partial q_{it}}{\partial p_t}\bigg|_{\text{“}Theory\text{”}} = 1 + \frac{1+0.037}{0.044} \approx 25 \tag{9}$$

This corresponds to the theory-implied elasticity in Figure 1.

If instead investors learn from prices, then price changes lead investors to revise their expectations of future payoffs. The second component in (8) is then positive, and this contributes to more inelastic demands. For example, if investors form expectations of future prices by assuming that $\mathbb{E}_t[p_{t+1}] = p_t$, then $\frac{\partial \mathbb{E}_t[\delta d_{t+1}+p_{t+1}]}{\partial p_t} = 1$, and the equivalent theoretical counterpart translates into a lower estimate:

$$-\frac{\partial q_{it}}{\partial p_t} = 1 + \frac{0.037}{0.044} \approx 1.8 \tag{10}$$

Intuitively, a price increase of this type plays a dual role: it makes the asset more expensive, leading investors to want to hold less of it, but also raises expectations of future payoffs, leading investors to want to hold more of it. This second force dampens investors' response to prices changes, contributing to a lower elasticity of demand (Bastianello and Fontanier 2025).

This discussion highlights two points. First, the relevant theoretical benchmark depends on how investors form beliefs. Whether current prices affect expectations of future payoffs determines what object a theoretical demand elasticity is intended to capture. Second, while the estimate in (10) does not fully close the gap between theory and empirical estimates, allowing current prices to affect expectations of future payoffs can be quantitatively meaningful.

More broadly, how investors form expectations determines both the demand elasticity they submit, and the conditions under which price multipliers identify that elasticity. The remainder of the paper studies these mechanisms under alternative models of belief formation.

3 Full Information Rational Expectations

To formalize these results, we revisit the more general demand function in Gabaix and Koijen (2023), and we highlight the role of full information rational expectations, which has implicitly been assumed in the literature so far. We then relax the assumption of investors having full information in Section 4, and of rational expectations in Section 5.

3.1 Setup

Assume that investors trade according to the following linearized asset demand function:

$$q_{it} = -(1-\theta)p_t + \kappa\hat{\pi}_{it} + f_{it} \tag{11}$$

where θ captures a local wealth-effect with respect to price changes, f_{it} is an exogenous investor-specific flow,[7] and $\hat{\pi}_{it}$ captures linearized changes in expected returns:[8]

$$\hat{\pi}_{it} = -(1+\delta)p_t + \mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}] \tag{12}$$

As well as being tractable, this demand function nests alternative frameworks.

Example (CARA Demand Function.). *Appendix A.2 shows how* (11) *nests a linearized CARA demand function with* $\kappa = \frac{1}{\delta}$ *and* $\theta = 0$.

Example (Gabaix and Koijen Demand Function.). *Gabaix and Koijen (2023) write demand in terms of portfolio weights:* $\frac{P_t Q_{it}}{W_{it}} = \theta \exp(\kappa\hat{\pi}_{it})$, *where* θ *is the baseline equity*

[7]Following Gabaix-Koijen, f_{it} can be interpreted as the proportional inflow into investor i's portfolio/fund relative to baseline wealth, with the cross-sectional measure normalized so that $f_t \equiv \int_{\mathcal{I}} f_{it} di$ is the aggregate equity flow (where di is equity-holding weighted).

[8]Specifically, for a price change that revalues existing holdings, investors who already hold the asset experience a change in wealth proportional to their pre-price-change portfolio share, which dampens the decline in share demand induced by the higher price.

share, which may reflect a portfolio-weight mandate. Equation (11) *is the corresponding linearized share demand.*[9]

Combining the two expressions in (11) and (12), we have that:

$$q_{it} = -\left(1 - \theta + \kappa(1+\delta)\right) p_t + \kappa \mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}] + f_{it} \tag{13}$$

Given this demand curve, we define the theoretical demand elasticity as the *slope* of investors' demand curve. Specifically, it measures the off-equilibrium response of holdings to changes in prices, holding fixed all other elements of investors' information set (in this case, flows and dividends):

$$-\frac{\partial q_{it}}{\partial p_t} = \left(1 - \theta + \kappa(1+\delta)\right) - \kappa \left(\frac{\partial \mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}]}{\partial p_t}\right) \tag{14}$$

If expectations of future payoffs do not causally depend on the current price, then the demand elasticity is given by: $\zeta \equiv 1 - \theta + \kappa(1+\delta)$. Demands are more elastic when the wealth effect θ is lower, and when the pass-through from beliefs to actions κ is higher. However, if expectations of future payoffs are influenced by current prices (e.g. due to learning from prices), then the second term in (14) is non-zero, and the demand elasticity has an additional term, as discussed in Section 2.2.

Studying this channel requires taking a stance on how investors form expectations. We start from the full information rational expectations benchmark, where investors

[9] The θ in the linearized demand in (11) comes from the wealth effect induced by price changes that revalue investors' existing holdings. Specifically, upon linearization, the Gabaix-Koijen demand function can be written as:

$$q_{it} = -p_t + w_{it} + \log(\theta) + \kappa \hat{\pi}_{it}$$

where $w_{it} = \theta p_t + f_{it}$ captures changes in the fund's wealth due to the revaluation of its existing holdings and investor flows. Taking derivatives with respect to the current price yields:

$$\partial q_{it}/\partial p_t = -1 + \partial w_{it}/\partial p_t + \kappa \partial \hat{\pi}_{it}/\partial p_t$$

If wealth is unchanged, as in stock splits, share holdings scale inversely with price, and dollar holdings are unchanged ($\partial w_{it}/\partial p_t = 0$). By contrast, for a price change that revalues existing holdings, investors already holding the asset experience a change in wealth proportional to the pre-price-change portfolio share: ($\partial w_{it}/\partial p_t = \theta$). Gabaix and Koijen (2023) discuss this wealth-effect by drawing on the distinction between Hicksian and Marshallian demand.

have perfect knowledge of all fundamentals. We then relax the assumptions of full information and of rational expectations in Sections 4 and 5, respectively.

3.2 Expectations of Future Payoffs

We start by deriving expected future payoffs under the full information rational expectations benchmark, where investors have full knowledge of the data generating process, and observe all lagged and current fundamentals.

Using (13), imposing market clearing ($\int q_{it}\,\mathrm{d}i = 0$), solving for the equilibrium price, and iterating forward, we obtain:

$$p_t = \sum_{\tau=0}^{\infty} \left(\frac{\kappa}{1-\theta+\kappa(1+\delta)} \right)^{\tau+1} \left(\delta \mathbb{E}_t[d_{t+\tau+1}] + \frac{\mathbb{E}_t[f_{t+\tau}]}{\kappa} \right) \tag{15}$$

where $f_{t+\tau} \equiv \int f_{i,t+\tau}\,\mathrm{d}i$ and $\mathbb{E}_t[\cdot] = \int \mathbb{E}_{it}[\cdot]\,\mathrm{d}i$.

Assumption 1. *Investors understand market clearing, and form expectations using accounting identities.*

If the above assumption holds, then:

$$\mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}] = \sum_{\tau=0}^{\infty} \left(\frac{\kappa}{1-\theta+\kappa(1+\delta)} \right)^{\tau} \left(\delta \mathbb{E}_{it}[d_{t+\tau+1}] + \frac{\mathbb{E}_{it}[f_{t+\tau+1}]}{1-\theta+\kappa(1+\delta)} \right) \tag{16}$$

To make further progress, we need to make assumptions about the underlying process of fundamentals, as well as investors' perception of how fundamentals evolve over time. Assume that both d_t and f_t evolve according to the following AR(1) processes:

$$f_t = (1-\phi_f) f_{t-1} + \epsilon_t \quad \text{and} \quad d_t = (1-\phi_d) d_{t-1} + \nu_t \tag{17}$$

where $\epsilon_t \overset{\text{iid}}{\sim} N(0, \tau_\epsilon^{-1})$ and $\nu_t \overset{\text{iid}}{\sim} N(0, \tau_\nu^{-1})$ are independent.

Assumption 2. *Investors have Full Information Rational Expectations (FIRE):*

i. know the process for the evolution of fundamentals: $\mathbb{E}_{it}[d_{t+\tau}] = (1-\phi_d)^\tau \mathbb{E}_{it}[d_t]$, $\mathbb{E}_{it}[f_{t+\tau}] = (1-\phi_f)^\tau \mathbb{E}_{it}[f_t]$, *ii. observe the full history of current and past fundamentals:* $\mathbb{E}_{it}[d_t] = d_t$, $\mathbb{E}_{it}[f_t] = f_t$.

If the above assumptions hold, then we can substitute $\mathbb{E}_{it}[d_{t+\tau}] = (1-\phi_d)^\tau d_t$ and $\mathbb{E}_{it}[f_{t+\tau}] = (1-\phi_f)^\tau f_t$ into (16), and solve for the infinite sum to obtain an expression of how investors form beliefs of expected future payoffs under full information rational expectations:

$$\mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}] = \left(\frac{(1-\phi_d)}{1 - \frac{\kappa(1-\phi_d)}{1-\theta+\kappa(1+\delta)}}\right)\delta d_t + \left(\frac{\frac{(1-\phi_f)}{1-\theta+\kappa(1+\delta)}}{1 - \frac{\kappa(1-\phi_f)}{1-\theta+\kappa(1+\delta)}}\right) f_t \tag{18}$$

Therefore, under full information rational expectations, fixing fundamentals also fixes investors' expectations of future payoffs.

3.3 Demand Elasticity and Price Multiplier

Substituting investors' expectations of future payoffs in (18) into their demand function in (13), we obtain the following demand function:

$$q_{it} = -\underbrace{(1-\theta+\kappa(1+\delta))}_{\text{slope}}\, p_t + \underbrace{\left(\frac{\kappa(1-\phi_d)}{1 - \left(\frac{\kappa(1-\phi_d)}{1-\theta+\kappa(1+\delta)}\right)}\right)\delta d_t + \left(\frac{\frac{\kappa(1-\phi_f)}{1-\theta+\kappa(1+\delta)}}{1 - \frac{\kappa(1-\phi_f)}{1-\theta+\kappa(1+\delta)}}\right) f_t + f_{it}}_{\text{intercept}} \tag{19}$$

Imposing market clearing, $\int q_{it}\,\mathrm{d}i = 0$, and using $\int f_{it}\,\mathrm{d}i = f_t$, we then obtain the following expression for equilibrium prices:

$$p_t = \left(\frac{\kappa(1-\phi_d)}{(1-\theta+\kappa(1+\delta)) - \kappa(1-\phi_d)}\right)\delta d_t + \left(\frac{1}{(1-\theta+\kappa(1+\delta)) - \kappa(1-\phi_f)}\right) f_t \tag{20}$$

Given the expressions in (19) and (20), we can now turn to understanding the relationship between demand elasticities and price multipliers.

Under full information rational expectations, investors have perfect knowledge of current and lagged prices, dividends, and flows. Given this information structure, the demand elasticity captures how investors' holdings respond to off-equilibrium changes in prices, while fixing all other elements that are part of their information set (dividends and flows). Therefore, the demand elasticity and price multiplier are given by:

$$\text{Demand Elasticity}: \quad -\frac{\partial q_{it}}{\partial p_t} = 1-\theta+\kappa(1+\delta) = \zeta^{GK}+\kappa \equiv \zeta \tag{21}$$

$$\text{Price Multiplier}: \quad \frac{dp_t}{df_t} = \frac{1}{\zeta-\kappa(1-\phi_f)} \equiv M(\phi_f) \tag{22}$$

where $\zeta^{GK} \equiv 1-\theta+\kappa\delta$ is the demand elasticity in Gabaix and Koijen (2023).

There are two points worth emphasizing at this stage. First, the demand elasticity does not capture the *equilibrium* response of quantities to changes in prices induced by changes in aggregate flows.[10,11] Rather, the demand elasticity is a *partial equilibrium object* which captures how much quantities would adjust due to an off-equilibrium change in prices, while keeping all fundamentals that are part of investors' information sets fixed. This is in contrast to the price impact, which is instead an *equilibrium* object. To consider equilibrium objects, we need to take derivatives with respect to exogenous rather than endogenous quantities.[12]

Second, there are two special cases of the expressions in (21) and (22) that are interesting to explore. We start by considering the case with completely transitory flows: $\phi_f = 1$. When this is the case $M(\phi_f = 1) = \frac{1}{\zeta}$, which reflects that, under full information rational expectations, our definition of demand elasticity captures the response of holdings to changes in prices, while holding expected future payoffs constant. Next, we consider the case with completely permanent flows: $\phi_f = 0$. When this is the case $M(\phi_f = 0) = \frac{1}{\zeta^{GK}}$, which illustrates that GK's demand elasticity corresponds to

[10]The equilibrium response of holdings to an exogenous flow shock would instead be: $\frac{\partial q_{it}}{\partial f_t} = -1 + \frac{\partial f_{it}}{\partial f_t}$.

[11]In equilibrium, investor i's demand curve is given by:

$$q_{it} = \kappa\left(\mathbb{E}_{it}[p_{t+1}+\delta d_{t+1}] - \mathbb{E}_t[p_{t+1}+\delta d_{t+1}]\right) + (f_{it}-f_t) \tag{23}$$

which also shows that for holdings to be stable, we either need investors to have homogeneous beliefs (and small differences in idiosyncratic flow shocks), or we need the pass-through from beliefs to holdings (and the corresponding demand elasticity) to be low (van der Beck et al. 2025). Under full information rational expectations, $\mathbb{E}_{it}[p_{t+1}+\delta d_{t+1}] = \mathbb{E}_t[p_{t+1}+\delta d_{t+1}]$, and the above expression simplifies to $q_{it} = f_{it} - f_t$. Therefore, in equilibrium, investors absorb exogenous flow shocks, while they are unresponsive to changes in fundamentals, which are correctly incorporated into prices, leaving expected returns unchanged.

[12]Intuitively, to study equilibrium responses when taking derivatives with respect to equilibrium objects such as prices, we need to know what caused that price change in the first place.

the inverse of the price impact for a fully permanent change in flows.

Moving away from these two corner cases, the expressions in (21) and (22) show how the demand elasticity is not necessarily equal to the inverse of the price impact. Importantly, this discrepancy is driven by the fact that the price impact confounds two effects: movements along the slope of the demand curve, and shifts in its intercept.

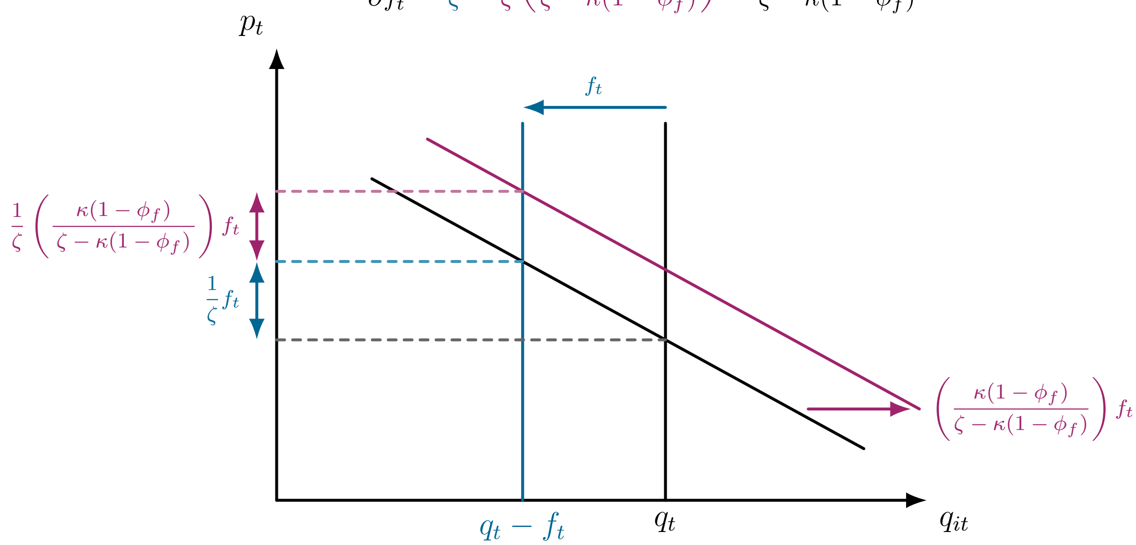
Specifically, starting from investors' demand function in (19), imposing market clearing, using the definition of ζ, and assuming $d_t = 0$, we can decompose the equilibrium price in two components:

$$p_t = \frac{1}{\zeta}\left(\frac{\kappa(1-\phi_f)}{\zeta-\kappa(1-\phi_f)}\right) f_t + \frac{1}{\zeta} f_t \tag{24}$$

where the first term captures the contribution of shifts in investors' expectations of future payoffs (the intercept shift), while the second term captures the price change required to absorb the change in net supply along the demand curve. Taking derivatives with respect to f_t then yields the decomposition illustrated in Figure 3, showing that the price multiplier combines movements along the demand curve with shifts in its intercept.

Figure 3: Price Multiplier – slope vs. intercept.

$$\frac{\partial p_t}{\partial f_t} = \frac{1}{\zeta} + \frac{1}{\zeta}\left(\frac{\kappa(1-\phi_f)}{\zeta-\kappa(1-\phi_f)}\right) = \frac{1}{\zeta-\kappa(1-\phi_f)}$$



Proposition 1. *Under Full Information Rational Expectations (FIRE), the inverse price multiplier identifies the demand elasticity if and only if flow shocks are completely transitory. When flow shocks are persistent, the inverse price multiplier does not identify the demand elasticity because the price multiplier reflects both movements along the demand curve and shifts in its intercept.*

When we distinguish between the slope and the intercept of the demand curve, the demand elasticity is fixed, even when the short-run and long-run multipliers vary. Given the above expressions, we can write the short-run multiplier as:

$$\frac{\partial p_t}{\partial f_t} = \frac{1}{\zeta - \kappa(1-\phi_f)} \tag{25}$$

while the long-run multiplier is given by:[13]

$$\frac{\partial p_{t+s}}{\partial f_t} = \frac{(1-\phi_f)^s}{\zeta - \kappa(1-\phi_f)} \propto \frac{\partial f_{t+s}}{\partial f_t} \tag{26}$$

As noted by Gabaix and Koijen (2023), the multiplier is larger when flows are more persistent, and "[to recover the demand elasticity,] empirical analyses estimating multipliers should ideally report also the speed of mean-reversion ϕ_f of the flows under study." Moreover, if the shock is transitory, the long-run multiplier is smaller than the short-run multiplier (van der Beck 2022), and it decays at the same rate as exogenous changes in flows.

Importantly, however, under full information rational expectations, the *slope* of the demand curve (and the demand elasticity) is the *same* for both long-run and short-run multipliers: the fact that multipliers decline with the horizon simply reflects gradually smaller shifts in the intercepts induced by the fading flow shocks.[14]

[13] Davis et al. (2026) show that observing price multipliers at multiple horizons can help separately identify demand elasticities and the persistence of the underlying shock. In the present benchmark, however, their rank condition is not satisfied, as $M_{h+1} = (1-\phi_f)M_h$, so the long-run multiplier is simply a scalar multiple of the short-run multiplier. Appendix C shows that extrapolative beliefs can break this relationship, potentially introducing additional variation for this exercise.

[14] The price impact with respect to shocks to d_t is instead fully characterized by a shift in the intercept (as the net supply in Figure 4 does not change with these shocks).

Corollary 1. *Under FIRE, dynamic price multipliers inherit the persistence of the underlying flow shock. When flows mean-revert, long-horizon multipliers decay at the same rate as flows. This reflects gradual shifts in the intercept of the demand curve, while the slope of the demand curve remains constant.*

The rest of this paper studies how different information structures and belief formation processes influence the mapping between elasticities and multipliers, which are informative of theory and empirical estimates of demand elasticities.

4 Incomplete Information Rational Expectations

So far, we have assumed not only that investors have rational expectations, but also that they have full information of fundamentals. In what follows, we maintain the assumption of rational expectations, but we relax the assumption of full information. To do so in a structured way, we import two concepts from the information economics literature: the Competitive Equilibrium (CE), and the Rational Expectations Equilibrium (REE). We start by studying the competitive equilibrium, where investors form expectations only using information from exogenous fundamentals, and then turn to the rational expectations equilibrium, where investors may also learn information from prices.

4.1 Competitive Equilibrium: No Learning from Prices

In this section we relax the assumption that investors have full information, while maintaining that they have rational expectations. Specifically, we relax Assumption 2.ii. and assume that investors don't perfectly observe current dividends and flows.

Starting from dividends, we assume that investors do not observe d_t, and instead observed noisy signals, such that their expectations of current dividends are given by:

$$\mathbb{E}_{it}[d_t] = d_t + u_{it} \tag{27}$$

where $u_{it} \overset{\text{iid}}{\sim} N(0, \tau_u^{-1})$ and $\int u_{it}\,\mathrm{d}i = 0$. Let $\hat{d}_t = \mathbb{E}_t[d_t]$ be the component of dividends that is revealed by average beliefs. In the simple signal structure considered here, average beliefs are unbiased, so $\hat{d}_t = d_t$.

Turning to flows, we introduce a distinction between observed and unobserved flow shocks. To do so, we let f_{it} denote investor-specific flow demand shifters whose aggregate component is observed before prices are set:

$$\int_i f_{it} di = \hat{f}_t, \qquad \hat{f}_t \equiv (1-\phi_f) f_{t-1} + \epsilon_t^o. \tag{28}$$

where ϵ_t^o is the observed flow innovation. In addition, there is an unobserved residual supply shock ϵ_t^u, which is realized before market clearing but is not part of investors' pre-price information sets.[15] We assume that ϵ_t^o, ϵ_t^u, and u_{it} are jointly-Gaussian, mean-zero, mutually orthogonal, and serially independent. Total aggregate flow pressure is then given by:

$$f_t = \hat{f}_t + \epsilon_t^u. \tag{29}$$

Before prices are set, investors observe $\hat{f}_t$, but not the realization of ϵ_t^u, so $\mathbb{E}_{it}[f_t] = \hat{f}_t$.

Given this information structure, investors' demand function is given by:

$$q_{it} = -\underbrace{(1-\theta+\kappa(1+\delta))}_{\text{slope}} p_t + \underbrace{\left(\frac{\kappa(1-\phi_d)}{1-\frac{\kappa(1-\phi_d)}{1-\theta+\kappa(1+\delta)}}\right)\delta\mathbb{E}_{it}[d_t] + \left(\frac{\frac{\kappa(1-\phi_f)}{1-\theta+\kappa(1+\delta)}}{1-\frac{\kappa(1-\phi_f)}{1-\theta+\kappa(1+\delta)}}\right)\mathbb{E}_{it}[f_t] + f_{it}}_{\text{intercept}} \tag{30}$$

Imposing market clearing $\int q_{it}\,\mathrm{d}i + \epsilon_t^u = 0$, we obtain the following equilibrium price function:

$$\begin{aligned} p_t = &\left(\frac{\kappa(1-\phi_d)}{(1-\theta+\kappa(1+\delta))-\kappa(1-\phi_d)}\right)\delta\hat{d}_t \\ &+ \left(\frac{1}{(1-\theta+\kappa(1+\delta))-\kappa(1-\phi_f)}\right)\hat{f}_t + \left(\frac{1}{1-\theta+\kappa(1+\delta)}\right)\epsilon_t^u \end{aligned} \tag{31}$$

When we compare (30) to (19), we see that while the observable component of flow shocks

[15] When we turn to the rational expectations equilibrium with learning from prices, ϵ_t^u plays the role of noisy residual supply, which prevents prices from being fully revealing.

does shift the intercept of investors' demand curves, the unobservable component does not.[16] This leads to different multipliers with respect to observable and unobservable shocks.

Let's start by considering the price multipliers for an observable flow shock, ϵ_t^o:

$$M^o \equiv \frac{\partial p_t}{\partial \epsilon_t^o} = \frac{1}{(1-\theta+\kappa(1+\delta)) - \kappa(1-\phi_f)} = \frac{1}{\zeta - \kappa(1-\phi_f)} \tag{32}$$

Just as under the full information rational expectations benchmark, the inverse observed-flow multiplier does not identify investors' submitted demand elasticity, as observable flow shock shift investors' demand curves.

Next, we can turn to the multiplier of a hidden contemporaneous flow innovation ϵ_t^u. Since investors do not observe ϵ_t^u, it does not directly shift their expectations of future payoffs. The price multiplier is then given by:

$$M^u \equiv \frac{\partial p_t}{\partial \epsilon_t^u} = \frac{1}{1-\theta+\kappa(1+\delta)} = (\zeta)^{-1} \tag{33}$$

Therefore, for hidden flow shocks, the inverse multiplier does recover the inverse demand elasticity: since the hidden shock does not directly shift the intercept of the demand curve, the whole price impact comes from movements along the demand curve.

Proposition 2. *Under incomplete information, the inverse price multiplier identifies the elasticity of the submitted demand curve if and only if the flow shock has no direct effect on investors' expectations of future payoffs. This condition is satisfied either when the shock is completely transitory or when it is outside investors' pre-price information set.*

Therefore, this section illustrates how once we are explicit about investors' information structure, the inverse multiplier may coincide with the demand elasticity, even for

[16] To develop intuition, and to keep notation simple within this framework, we are abstracting from the fact that investors face greater uncertainty under CE, relative to the FIRE benchmark. A natural way to incorporate this in the current framework would be to let κ be decreasing in investors' uncertainty of next period payoffs, such that $\kappa^{CE} < \kappa^{FIRE}$. This would then translate in the CE having a lower demand elasticity and greater multiplier relative to the FIRE benchmark.

flow shocks that are not purely transitory. However, under this information structure, we still need these shocks to leave expected future payoffs unchanged. The next section illustrates how this latter condition is also no longer necessary if investors learn information from prices.

4.2 Rational Expectations Equilibrium: Learning from Prices

So far we have assumed that investors' expectations of future payoffs are not causally influenced by contemporaneous changes in prices. In what follows we consider how demand elasticities and multipliers change once we consider the Rational Expectations Equilibrium (REE), where investors have rational expectations and also learn fundamental information from prices.

Specifically, the expression for the equilibrium price in (31) shows how prices aggregate investors' private signals, and reveal information about $\hat{d}_t$. Therefore, investors can obtain a more accurate estimate of d_t by learning information from prices.

Specifically, investors can invert the market clearing price function in (53) to obtain the following noisy signal of expected future payoffs:

$$s_t \equiv \left(\frac{\zeta}{\kappa}p_t - \frac{1}{\kappa}\hat{f}_t\right) = \mathbb{E}_t[p_{t+1} + \delta d_{t+1}] + \frac{1}{\kappa}\epsilon_t^u \tag{34}$$

When flows are fully observed (such that $\epsilon_t^u = 0$), prices become fully revealing of market participants' expectations of future payoffs, as shown in Appendix A.3. Otherwise, they are only partially revealing, but investors can still infer a noisy signal from them.

Let $\mathbb{E}_{it}^{-p}[\cdot]$ denote investor i's expectation before conditioning on the current price. In a linear Gaussian equilibrium, investor i's posterior expectation of $\mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}]$ can be written as:

$$\mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}] = \mathbb{E}_{it}^{-p}[p_{t+1} + \delta d_{t+1}] + g\left(s_t - \mathbb{E}_{it}^{-p}[p_{t+1} + \delta d_{t+1}]\right), \tag{35}$$

where g is the equilibrium Kalman gain placed on the price signal. This expression shows how investors use a weighted average of the signal and the prior, where the weight on the signal is increasing in its precision relative to the prior. Substituting the updating rule into investors' demand functions gives:

$$q_{it} = \underbrace{-(1-g)\zeta}_{\text{slope}} p_t + \underbrace{\kappa(1-g)\mathbb{E}_{it}^{-p}[p_{t+1} + \delta d_{t+1}] - g\mathbb{E}_{it}^{-p}[f_t] + f_{it}}_{\text{intercept}} \tag{36}$$

where in our case $\mathbb{E}_{it}^{-p}[f_t] = \hat{f}_t = (1-\phi_f)f_{t-1} + \epsilon_t^o$. Taking derivatives with respect to prices then yields the following demand elasticity:

$$\zeta^{PR}(g) \equiv -\frac{\partial q_{it}}{\partial p_t} = (1-g)\zeta \tag{37}$$

If prices are uninformative, $g = 0$, then investors only condition on their own private information, and the demand elasticity is equal to ζ, as in the competitive equilibrium. By contrast, in the limit as prices become fully informative relative to the prior, $g \to 1$, investors put full weight on the signal inferred from prices, and demand becomes perfectly inelastic, as in the fully revealing rational expectations equilibrium shown in Appendix A.3. Therefore, the partially revealing elasticity interpolates between the CE elasticity and the fully revealing REE elasticity. Within intermediate cases, investors load more on prices when they are more informative relative to their prior beliefs, and greater loadings translate into more inelastic markets.

The noisier the signal investors are able to extract from prices (relative to their prior), the less will they condition on the current price. This contributes to markets being more elastic than under the fully revealing rational expectations equilibrium. More generally, demand elasticities vary with the information environment.[17]

Proposition 3. *Under a partially revealing rational expectations equilibrium, demand becomes more inelastic as prices become more informative relative to investors' prior information.*

[17]This could be tested empirically, for example by using measure of price informativeness (Dávila and Parlatore (2026), Bai et al. 2016).

Turning to the mapping between elasticities and multipliers, this once again depends on whether the flow shock is part of investors' pre-price information set. Similarly to the analysis in Section 4.1, while the multiplier of observable shocks confounds movements along the demand curve with shifts in its intercept, the impact multiplier of unobservable shocks identifies the inverse of the relevant demand elasticity, which in this case is given by: $(1-g)\zeta$.

Finally, equilibrium holdings are given by:

$$q_{it} = \kappa(1-g)\left(\mathbb{E}_{it}^{-p}[p_{t+1} + \delta d_{t+1}] - \mathbb{E}_{t}^{-p}[p_{t+1} + \delta d_{t+1}]\right) + (f_{it} - f_t) \tag{38}$$

When investors load more on the common signal they learn from prices (higher g), disagreement falls, and holdings are more stable. Therefore, learning from prices lends itself to providing a joint explanation for why markets may be excessively volatile while portfolio holdings are relatively stable (van der Beck et al. 2025).

4.3 Taking Stock

Departing from the full information rational expectations benchmark highlights two points about the conditions under which inverse multipliers identify demand elasticities. First, flow shocks need not be transitory if they do not enter investors' pre-price information sets. Second, if investors learn from prices, shocks need not leave expected future payoffs unchanged. Instead, any effect on expected future payoffs must operate through equilibrium prices, rather than directly through investors' pre-price information. The remainder of this section summarizes these two insights in a more general framework.

More generally, let z_t denote any shock, let $f_t(z_t)$ denote its direct contribution to aggregate flows, and write $\mu_t(p_t, z_t) \equiv \mathbb{E}_t[p_{t+1} + \delta d_{t+1} \mid p_t, I_t^{-p}]$, where I_t^{-p} captures investors' information sets before observing the current price in period t. Aggregate market clearing can then be written as:

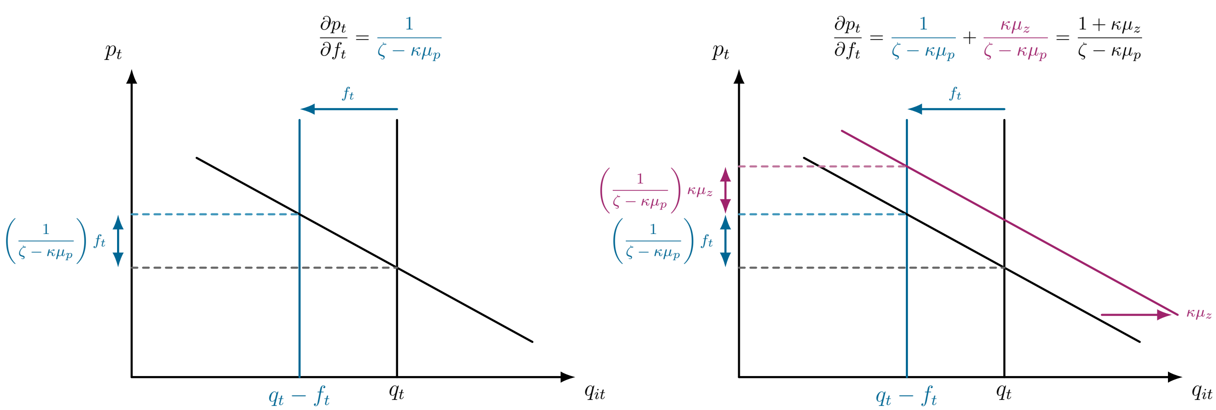
$$0 = -\zeta p_t + \kappa \mu_t(p_t, z_t) + f_t(z_t). \tag{39}$$

Totally differentiating gives:

$$\frac{dp_t}{dz_t} = \frac{f_z + \kappa\mu_z}{\zeta - \kappa\mu_p}, \tag{40}$$

where μ_z denotes the direct effect of the shock on expected future payoffs, holding the price fixed. The denominator is the relevant demand elasticity, while the numerator captures both the direct flow effect and any shift in the demand intercept. For a unit hidden supply shock, $f_z = 1$ and $\mu_z = 0$, so the inverse multiplier recovers the demand elasticity. For an observed shock, μ_z may instead be nonzero, and the multiplier also reflects an intercept shift, as shown in Figure 4.

Figure 4: Price multiplier: unobserved vs. observed flow shocks.



(a) Unobserved shock, $\mu_z = 0$

(b) Observed shock, $\mu_z \neq 0$

This distinction is important for identification. If the target is the fixed-belief slope ζ, one needs price variation that leaves expected future payoffs unchanged (van Binsbergen et al. 2026). If instead the target is the slope of the demand curve investors actually submit when prices are informative, then price-induced belief revisions are part of the slope. In that case, the relevant elasticity is $\zeta - \kappa\mu_p$, and a hidden supply shifter observed by the econometrician but not by investors can identify this price-learning elasticity. The key requirement is not that expected future payoffs remain fixed, but that any change in expected future payoffs operates through the price rather than through investors' non-price information.

Finally, notice that while the elasticity of investors' submitted demand function, $(1-g)\zeta$, varies with the informativeness of prices, it is not necessarily less portable than ζ. After all, $\zeta \equiv 1-\theta+\kappa(1+\delta)$ also varies with κ (as well as the wealth effect θ). To the extent that investors trade more aggressively on their beliefs when they face lower uncertainty, κ may depend on investors' perceived return variance, which is itself a function of the informativeness of prices (and of g). Consequently, demand elasticities are information-dependent objects.

This does not mean that estimated elasticities cannot be used for counterfactuals. Rather, counterfactuals should be evaluated using elasticities estimated in similar information environments.[18] An important exception arises when shocks and policies themselves alter demand elasticities by changing the informativeness of prices (Bond and Goldstein 2015).[19] In these cases, counterfactuals should account for the resulting change in the information environment.

4.3.1 Applications: Interpreting Flow Multipliers

The decomposition in (40), and the distinction between observable and unobservable shocks, can be used to interpret what the multipliers in Figure 1 identify. These differ not only because they use different assets, horizons, or levels of aggregation, but also because they are characterized by different information structures.[20]

For example, index-inclusions are public events, and can therefore be interpreted through the lens of observed flow shocks, which alter investors' pre-price information sets. In these instances, the estimated multipliers are the result of both movements along the demand curve, and shifts in its intercept. Instead, designs that exploit flow-induced trading or mutual fund flows are closer to the hidden-flow benchmark. The econometrician constructs stock-level flow shocks from fund flows and portfolio holdings.

[18]Moreover, constructing counterfactual equilibrium outcomes requires understanding not only how elastic markets are, but also how the shock or policy of interest affects investors' expectations.

[19]For other examples of how policy may impact demand elasticities, see also Caballero and Simsek (2021), Brunnermeier et al. (2022), Gaballo and Galli (2025), Fontanier (2026), among others.

[20]Our analysis focuses on macro-elasticities, but the distinction between observable and unobservable shocks, and the role of learning from prices can both be extended to the analysis of elasticities at other levels of aggregation as well.

To the extent that these residual shocks are not part of investors' pre-price information sets, their inverse multipliers may identify the relevant demand elasticity.

Take, for example, the granular instrumental variable (GIV) methodology in Gabaix and Koijen (2023). Assume for simplicity that investors do not learn information from prices, so that the relevant demand elasticity is ζ.[21] Changes in sector i's demand can be written as:

$$\Delta q_{it} = -\zeta \Delta p_t + \xi_{it}, \tag{41}$$

where ξ_{it} collects sector i's non-price demand shifters:

$$\xi_{it} \equiv \Delta f_{it} + \kappa \left(\Delta \mathbb{E}_{it}^{-p}[p_{t+1}] + \delta \Delta \mathbb{E}_{it}^{-p}[d_{t+1}] \right) \tag{42}$$

To estimate the demand elasticity of sector i, the GIV methodology uses residualized idiosyncratic demand shocks to other sectors as instruments for prices. Intuitively, the instrument needs to affect demand of sector i only through the equilibrium price. These shocks are then the sector-level analogue of the unobserved residual supply shock ϵ_t^u above: from the perspective of sector i, they generate residual flow pressure without directly shifting sector i's demand intercept.

The information-set interpretation of this exclusion restriction is that the leave-one-out shock must not directly enter sector i's pre-price information set. Equivalently, it must not directly shift sector i's non-price demand shifter ξ_{it}. Under full information rational expectations, this condition generally fails for persistent shocks: sector i observes the shock, understands its implications for future resale values, and therefore revises $\mathbb{E}_{it}^{-p}[p_{t+1} + \delta d_{t+1}]$. In that case, the instrument moves both prices and sector i's demand intercept. Under incomplete information, by contrast, the residualized leave-one-out shock may be outside sector i's pre-price information set.[22] Then it moves sector i's demand only through the equilibrium price, just as ϵ_t^u does in the residual-supply

[21]With learning from prices, we can apply the same argument, and the demand elasticity that is identified is $(1-g)\zeta$.

[22]Notice how the shock need not be hidden from the sector where it originates. It only needs to be outside the pre-price information set of the sector whose elasticity is being estimated.

benchmark. When this is the case, the GIV estimator identifies the submitted demand elasticity. The identifying restriction is no longer that shocks must be completely transitory and leave investors' expectations of future resale values unchanged. Rather shocks may be persistent and affect investors' expectations of future resale values, as long as they do so through their effect on equilibrium prices.

Finally, notice that the distinction across flow-shock designs is not that they necessarily correspond to different demand elasticities. Rather, they differ in whether the identifying variation reveals the relevant elasticity or combines movements along the demand curve with shifts in its intercept.

5 Biased Beliefs

Having shown how investors' information structure and whether they learn from prices shapes both the interpretation of inverse multipliers and the determinants of inelastic markets, we now extend the analysis to allow for biased beliefs. We study two classes of belief distortions that mirror the distinction between the competitive equilibrium and the rational expectations equilibrium: mislearning from exogenous fundamentals and mislearning from prices (Bastianello and Fontanier 2025). We show that while mislearning from fundamentals primarily shifts the intercept of investors' demand curves, mislearning from prices affects demand elasticities as well. This distinction proves helpful in understanding the role of beliefs in jointly explaining the evidence on excess volatility and inelastic markets, and illustrates how jointly studying prices and quantities can be informative of the economic mechanisms underlying fluctuations in asset prices.

5.1 Mislearning from Fundamentals

We start by studying mislearning from fundamentals, in which investors' expectations are distorted by how they process exogenous quantities, such as dividends and flows.

These biases can be modeled in a number of other different ways.[23] For example,

[23]Throughout this section we denote with a $\tilde{}$ investors' beliefs about a variable. For example $\tilde{\phi}_f$

allowing for traders to have misspecified perceptions of the persistence of flows or dividends, $\tilde{\phi}_f \neq \phi_f$, $\tilde{\phi}_d \neq \phi_d$, may capture over- or under-extrapolation of fundamentals (Nagel and Xu 2022), $\tilde{u}_{it} = \psi_u u_{it}$ may capture various forms of biases in Bayesian updating, such as overconfidence in one's own private information (Daniel et al. 2001), $\tilde{\epsilon}_t{}^o + \tilde{e}_{it} = \psi(\epsilon_t^o + e_{it})$ may capture biases where investors over or underreact to both common and idiosyncratic components, such as diagnostic expectations or inattention (Bordalo et al. 2019, Gabaix 2019). Within this framework, $\tilde{\phi}_d < \phi_d$, $\tilde{\phi}_f < \phi_f$, $\psi_u > 1$, $\psi > 1$ generate overreaction, while reversing the inequalities yields underreaction.

Substituting these beliefs in (30) shows how mislearning from exogenous fundamentals change the intercept of the demand curve, but not its slope. Whenever $\tilde{\phi}_f \neq \phi_f$, $\tilde{\phi}_d \neq \phi_d$, or $\tilde{u}_{it} \neq u_{it}$, mislearning from fundamentals affects the price multiplier, even though the demand elasticity is unaffected by this bias. For example, over-extrapolating flows ($\tilde{\phi}_f < \phi_f$) or cash-flows ($\tilde{\phi}_d < \phi_d$) induces a greater shift in the demand curve and a greater price impact than under the rational benchmark. Therefore, over-extrapolating fundamentals can contribute to excess volatility, but leaves the evidence on inelastic markets unexplained.

Proposition 4. *Mislearning from fundamentals shifts the intercept of investors' demand curves, but leaves their slope unchanged. Consequently, it can generate excess volatility but does not make markets more inelastic.*

5.2 Mislearning from Prices

Next, we turn to studying mislearning from prices, which arises when investors use a misspecified mapping to infer information from equilibrium outcomes.[24] Rational learning in Section 4.2 required that $\tilde{\mu}_p = \frac{g\zeta}{\kappa}$, which reflects two aspects of price learning: $\frac{\zeta}{\kappa}$ captures the mapping investors use to extract information from prices in (34), while g captures investors' perception of how informative prices are relative to the prior. When

refers to investors beliefs about the persistence of flows.

[24]Examples include DeMarzo et al. (2003), Eyster and Rabin (2005), Malmendier and Nagel (2011), Barberis et al. (2018), Enke and Zimmermann (2019), Han et al. (2022), Barberis and Jin (2023), Jiang et al. (2025), Bastianello and Fontanier (2025), Bohren and Hauser (2025), among others.

$\tilde{\mu}_p < \frac{g\zeta}{\kappa}$, investors underreact to information, and markets are more elastic. This may arise either if the signal investors extract from prices is smaller than in reality, or if they think the signal is less informative. Conversely, $\tilde{\mu}_p > \frac{g\zeta}{\kappa}$ leads to overreaction in beliefs, and more inelastic demand curves.

Proposition 5. *Mislearning from prices alters the slope of investors' demand curves. Consequently, it can generate both excess volatility and more inelastic markets.*

Moreover, this distinction has important implications for which shocks are amplified. When investors do not learn from prices, unobservable shocks do not directly affect their expectations of future payoffs, so mislearning from fundamentals can amplify only observable shocks. By contrast, because mislearning from prices changes the slope of the submitted demand curve, it amplifies both observable and unobservable shocks (Mendel and Shleifer 2012). Consistent with this mechanism, Chaudhry (2025) finds that sell-side analysts' cash-flow expectations respond to price changes that are unrelated to cash-flow news, suggesting that this channel may be quantitatively important.

Corollary 2. *While mislearning from fundamentals can only amplify observable shocks, mislearning from prices may amplify both observable and unobservable shocks.*

Appendix C shows how studying the dynamics of prices and quantities may help distinguish alternative mechanisms. Under rational expectations, dynamic multipliers inherit the persistence of the underlying fundamentals, and investors are either momentum or contrarian with respect to both short-run and long-run returns. By contrast, models of extrapolative beliefs can generate additional persistence beyond that of fundamentals, leading investors to trade contrarian with respect to short-run returns and momentum with respect to long-run returns, consistent with empirical evidence on retail investors' trading behavior (Kogan et al. 2024, Bastianello and Fontanier 2026, Jin and Peng 2026).

Taken together, these results suggest that the source of market inelasticity matters as much as its magnitude. From a policy perspective, identifying why markets are inelastic is as important as measuring how inelastic they are. If inelasticity reflects learning from prices, policies that move prices also alter investors' beliefs, creating an additional channel through which they affect equilibrium outcomes. By contrast, if it reflects low pass-through from beliefs to holdings or other mechanisms, the same intervention may have very different equilibrium effects.

6 Conclusions

This paper studies how different forms of belief formation contribute to understanding the evidence on inelastic markets, both in terms of specifying which object empirical estimates are able to identify, and in exploring the sources of inelasticity. Jointly studying prices and quantities can be informative of how investors form beliefs, and of the economic mechanisms that drive asset pricing fluctuations.

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A Proofs and Derivations

A.1 Linearizing Expected Returns

We derive the linearized expression for expected returns used in the main text.

Start from the definition of gross expected returns:

$$1 + \pi_{it} \equiv \frac{E_t^i[P_{t+1} + D_{t+1}]}{P_t}. \tag{43}$$

We log-linearize around a steady state with constant prices and dividends. Let

$$P_t = \bar{P}(1 + p_t), \qquad D_{t+1} = \bar{D}(1 + d_{t+1}), \tag{44}$$

where p_t and d_{t+1} denote small deviations from steady state. Define the steady-state dividend-price ratio as

$$\delta \equiv \frac{\bar{D}}{\bar{P}}. \tag{45}$$

Under a zero-growth steady state, $\bar{P}_{t+1} = \bar{P}_t = \bar{P}$, so we can write

$$1 + \pi_{it} = \frac{E_t^i[\bar{P}(1 + p_{t+1}) + \bar{D}(1 + d_{t+1})]}{\bar{P}(1 + p_t)}. \tag{46}$$

Dividing numerator and denominator by $\bar{P}$ gives

$$1 + \pi_{it} = \frac{1 + \delta + E_t^i[p_{t+1}] + \delta E_t^i[d_{t+1}]}{1 + p_t}. \tag{47}$$

Using the first-order approximation $(1 + p_t)^{-1} \approx 1 - p_t$, we obtain

$$1 + \pi_{it} \approx \left(1 + \delta + E_t^i[p_{t+1}] + \delta E_t^i[d_{t+1}]\right)(1 - p_t). \tag{48}$$

Dropping second-order terms yields

$$1 + \pi_{it} \approx (1 + \delta) + E_t^i[p_{t+1}] + \delta E_t^i[d_{t+1}] - (1 + \delta)p_t. \tag{49}$$

Rearranging, we obtain the linearized expression used in the main text:

$$1 + \pi_{it} \approx (1 + \delta) - (1 + \delta)p_t + E_t^i[p_{t+1} + \delta d_{t+1}]. \tag{50}$$

Taking derivatives with respect to p_t then gives

$$\frac{\partial \pi_{it}}{\partial p_t} = -(1 + \delta) + \frac{\partial E_t^i[p_{t+1} + \delta d_{t+1}]}{\partial p_t}. \tag{51}$$

The linearization highlights two forces through which prices affect expected returns. Holding expectations fixed, a higher current price lowers expected returns mechanically, generating the term $-(1+\delta)p_t$. In addition, if prices affect beliefs about future payoffs, then $E_t^i[p_{t+1} + \delta d_{t+1}]$ will also vary with p_t. This second channel is absent in a standard competitive equilibrium without learning from prices, but becomes central when investors extract information from prices.

A.2 Linearizing CARA Utility

Taking a first order Taylor series approximation of CARA utility, with $\mathbb{V} = \mathbb{V}[\pi_t]$ we have:[25]

$$
\begin{aligned}
Q_t &= \frac{1}{A\mathbb{V}P_t}\left(\frac{\mathbb{E}_t[P_{t+1} + D_{t+1}] - P_t}{P_t}\right) \\
&= \frac{\mathbb{E}_t\left[\bar{P}_{t+1}(1+p_{t+1}) + \bar{D}_{t+1}(1+d_{t+1}) - \bar{P}_t(1+p_t)\right]}{A\mathbb{V}\bar{P}_t^2(1+p_t)^2} \\
&\approx \frac{1}{A\mathbb{V}\bar{P}_t}\left(\frac{\mathbb{E}_t[\bar{P}_{t+1} + \bar{D}_{t+1}] - \bar{P}_t}{\bar{P}_t} - \frac{2(\mathbb{E}_t[\bar{P}_{t+1} + \bar{D}_{t+1}] - \bar{P}_t)}{\bar{P}_t}p_t + \frac{\mathbb{E}_t[\bar{P}_{t+1}p_{t+1}] + \mathbb{E}_t[\bar{D}_{t+1}d_{t+1}] - \bar{P}_t p_t}{\bar{P}_t}\right) \\
&= \bar{Q}_t - \frac{1}{A\mathbb{V}\bar{P}_t}\left(2\delta p_t - \mathbb{E}[p_{t+1} + \delta d_{t+1}] + p_t\right) = \bar{Q}_t - \frac{1}{A\mathbb{V}\bar{P}_t}\left(\delta p_t + (1+\delta)p_t - \mathbb{E}[p_{t+1} + \delta d_{t+1}]\right)
\end{aligned}
$$

Let $q_t \equiv \frac{Q_t - \bar{Q}_t}{\bar{Q}_t}$ and $\bar{Q}_t = \frac{1}{A\mathbb{V}P_t}\left(\frac{\mathbb{E}[\bar{D}]}{\bar{P}}\right) = \frac{\delta}{A\mathbb{V}P_t}$, where δ is the average dividend yield. Then:

$$
q_t = -p_t - \left(\frac{1+\delta}{\delta}\right)p_t + \left(\frac{1}{\delta}\right)\mathbb{E}[p_{t+1} + \delta d_{t+1}] = -p_t + \frac{1}{\delta}\hat{\pi}_t \tag{52}
$$

This is nested in the linearized demand function in Gabaix and Koijen (2023), with $\theta = 0$ and $\kappa = \frac{1}{\delta}$ (and no flows).

[25] We let $\mathbb{V} = \mathbb{V}[\pi_t]$, rather than $\mathbb{V} = \mathbb{V}[D_{t+1} + P_{t+1}]$ because empirically it is more realistic to think of as the variance of expected returns rather than the variance of expected future payoffs as being constant over time.

A.3 REE with Fully Revealing Prices

When both f_t and ϵ_t^u are known, prices are in fact fully revealing of the underlying fundamentals. Therefore, investors can obtain an estimate of d_t by learning from prices.

To solve for the rational expectations equilibrium, we proceed in two steps. First, we specify what mapping traders use to learn information from prices. Second, we study the properties of traders' demand functions when they do so.

Under rational expectations, investors learn from prices using the right mapping from prices to the market's expectations of future payoffs.[26] In equilibrium, prices are given by:

$$p_t = \frac{\kappa}{\zeta}\mathbb{E}_t[p_{t+1} + \delta d_{t+1}] + \frac{1}{\zeta} f_t \tag{53}$$

Inverting this price function to determine market participants' expectations of future payoffs yields:

$$\mathbb{E}_t[p_{t+1} + \delta d_{t+1}] = \frac{\zeta}{\kappa} p_t - \frac{1}{\kappa} f_t \tag{54}$$

Under common knowledge of rationality, traders understand that prices always aggregate information correctly and efficiently. Therefore, they adopt the expectations in (54). Substituting these expectations into their demand functions, we obtain:

$$q_{it} = -\zeta p_t + \kappa \mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}] + f_{it} = f_{it} - f_t \tag{55}$$

Therefore, traders' demand functions in these instances are insensitive to price changes. Formally:

$$\frac{\partial q_{it}}{\partial p_t} = -\zeta + \kappa \frac{\partial \mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}]}{\partial p_t} = -\zeta + \kappa \left(\frac{\zeta}{\kappa}\right) = 0 \tag{56}$$

Since traders think prices are always right, they are willing to absorb any changes in aggregate flows, and are completely unresponsive to changes in prices. Formally, there are two competing forces at play (Bastianello and Fontanier 2025). First, prices have

[26] We could have also solved this by inverting prices to obtain d_t, and then used that to recreate investors' expectations of next period payoffs $\mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}]$. This is equivalent to the derivation in the text, as the mapping from d_t to $\mathbb{E}_{it}[p_{t+1} + \delta d_{t+1}]$ is deterministic and common knowledge in this setting.

their standard role as a measure of scarcity: when the asset becomes more expensive, traders wish to hold less of it. Second, when investors learn from prices, prices have an additional informational role: when the asset price increases, investors attribute this to positive news about expected future payoffs, which induces them to want to hold more of the asset. Under the rational expectations equilibrium, these forces perfectly cancel out, leading to perfectly inelastic markets.

Moreover, since investors are able to recover d_t precisely from (fully revealing) prices, the price impact is the same as under the full information rational expectations benchmark. Prices are consistent with correct beliefs about fundamentals, and investors' expected returns are constant, so their holdings do not respond to changes in prices.

B Low Pass-through from Beliefs to Holdings

Empirical evidence suggests that the pass-through of beliefs to holdings may be quantitatively important, albeit heterogeneous across investors. Using account-level data from Vanguard retail investors, Giglio et al. (2021) document low pass-through from beliefs to portfolio shares relative to frictionless benchmarks. In contrast, Dahlquist and Ibert (2023) find that capital flows across equity funds respond more strongly to expected returns.[27]

B.1 CARA Utility

Under CARA utility, the demand for the risky asset is proportional to expected returns. Taking the derivative of (1), the semi-elasticity of demand with respect to changes in

[27] Among other papers that have explored these channels, Greenwood and Shleifer (2014), Bastianello (2022), Andolfatto and Bastianello (2025), Andonov et al. (2025), find that flows are positively related to return expectations, and Charles et al. (2024), Andries et al. (2025), Yang (2023), and Hartzmark and Sussman (2025) study the pass-through from beliefs to holdings via online experiments, and Davis (2025) takes a complementary model-based approach and shows that standard quantitative strategies generate a low pass-through from beliefs to holdings due to risk considerations and the noisy nature of return signals.

expected returns is given by:

$$\frac{\partial q_t}{\partial \pi_t} = \frac{1}{\pi_t} \tag{57}$$

Therefore, the only way for this channel to contribute to low demand elasticity is for investors to have implausibly high expected returns. Empirically, this doesn't seem to be the case, as investors' expected returns are in the right ballpark, on average (Giglio et al. 2021). This condition also illustrates how under CARA utility a low pass-through from beliefs to holdings in *levels* is not enough to generate a low *elasticity* of demand.[28,29]

For example, even modeling inertia by multiplying expected returns by a factor $0 < \alpha < 1$ (as in some models of inattention) will limit the pass-through from beliefs to actions in levels, but cannot impact demand elasticities without also predicting implausibly high expected returns in equilibrium:

$$Q_{it} = \frac{\alpha \pi_{it}}{P_t A \mathbb{V}} \implies q_{it} = \log(\alpha) + \log(\pi_{it}) - p_t - \log(A\mathbb{V}) \implies \frac{\partial q_{it}}{\partial \pi_{it}} = \frac{1}{\pi_{it}} \tag{59}$$

For a limited pass-through to generate meaningful inelasticity without requiring implausibly high expected returns, we can't rely on modeling return expectations alone. Rather, we need to consider alternative utility specifications that break the proportionality between holdings and expected returns. Appendix B.2

The next section shows how this can for example be achieved via fixed mandates or exponential utility functions (Pavlova and Sikorskaya 2023, Gabaix and Koijen 2023).

[28]For example, Giglio et al. (2021) show that the sensitivity of portfolios to expectations in levels appears muted relative to a frictionless portfolio choice model. They document this by estimating the following pass-through in levels:

$$\frac{Q_{it}P_t}{W_t} = \frac{\pi_{it}}{\gamma \mathbb{V}} \implies \frac{\partial \left(\frac{Q_{it}P_t}{W_t}\right)}{\partial \pi_{it}} = \frac{1}{\gamma \mathbb{V}} \tag{58}$$

where W_{it} is agent i's wealth at time t, and $\gamma \equiv W_{it}A$ is the coefficient of relative risk aversion. However, comparing (57) to (58) makes clear that these are two very distinct objects. In fact, the variance component is totally absent in the semi-elasticity of demand with respect to changes in expected returns, as this term becomes additive in (1) once we take logs. Therefore, under CARA utility, a low pass-through in levels does *not* contribute to a low elasticity of demand.

[29]By taking logs, the expression in (1) clearly shows how the pass-through of expected returns to the equity share enters additively, and therefore does not influence the semi-elasticity of demand with respect to expected returns.

B.2 Demand Function and Pass-through of Beliefs to Holdings

In this section we explore how braking the proportionality between holdings and expected returns allows a low pass-through from beliefs to holdings to also impact demand elasticities.

Additive Demand. One way to achieve a limited pass-through both in levels and in the semi-elasticity under consideration is to model the average asset demand of a group of investors as:[30]

$$Q_{it} = (1-\alpha)\theta + \alpha\left(\frac{\pi_{it}}{P_t A \mathbb{V}}\right) \tag{60}$$

where $0 < \alpha < 1$ implies a low pass-through in levels, and the additive nature of the demand function now allows this to also affect the demand elasticity. This specification nests fixed mandates with $\alpha = 0$ (Pavlova and Sikorskaya 2023), and captures inattention to expected returns or fixed adjustment costs when $0 < \alpha < 1$ (the lower α is, the more inattentive investors are).

A more general representation of this specification is given by:

$$Q_{it} = \theta + \kappa\pi_{it} \tag{61}$$

The pass-through in levels, and the semi elasticity of demand with respect to expected returns are then given by:

$$\frac{\partial Q_{it}}{\partial \pi_{it}} = \kappa \quad \text{and} \quad \frac{\partial q_{it}}{\partial \pi_{it}} = \frac{1}{\frac{\theta}{\kappa} + \pi_{it}} \tag{62}$$

so that a higher θ and a lower κ both contribute to more inelastic markets. A higher θ increases the fraction of demand that comes from the fixed mandate, which is the

[30]This specification should be interpreted as a reduced-form average demand schedule, rather than as a literal individual-level policy under inattention or fixed adjustment costs. At the individual level, these frictions would typically generate lumpy adjustment: investors keep their previous or default holdings until a random or state-dependent adjustment date, and then reset toward the frictionless demand $Q^*_{it} = \pi_{it}/(P_t AV)$. For example, if investor adjust with probability α, choose Q^*_{it} when they adjusts, and otherwise hold θ, then average demand is given by (60). Thus, α can be interpreted as the fraction of investors who are attentive or able to adjust in a given period.

inelastic part of the demand function. A lower κ reduces the responsiveness of holdings to expected returns, which now also contributes to more inelastic demand. A downside of this approach is that this demand function is less tractable when working in logs.

Gabaix and Koijen (2023). An alternative asset demand function, which is tractable in logs is the one used in Gabaix and Koijen (2023):

$$Q_{it} = \theta \exp(\kappa \pi_{it}) \tag{63}$$

where $\kappa = 0$ nests fixed mandates. One of the advantages of this type of utility function is that log holdings are then linear in expected returns.

Given this demand function, the pass-through in levels and the semi-elasticity of demand with respect to expected returns are then given by:

$$\frac{\partial Q_{it}}{\partial \pi_{it}} = \kappa Q_{it} \quad \text{and} \quad \frac{\partial q_{it}}{\partial \pi_{it}} = \kappa \tag{64}$$

The lower κ is, the less responsive are holdings to expected returns, and the lower the semi-elasticity of holdings. Therefore, a low pass-through from holdings to expected returns now also contributes to more inelastic markets.

C Dynamic Multipliers, Trading Behavior, and Extrapolative Beliefs

In this section we show how more dynamic forms of learning may allow us to further distinguish the two classes of biases we have considered to far. Specifically, we consider two forms of extrapolative beliefs: extrapolation from past fundamentals, and extrapolation from past prices. To keep the type of bias similar, we consider cases where investors extrapolate the same number of lags of either fundamentals or prices. To simplify notation, we assume that $\mathbb{E}_t[d_{t+1}] = 0$, such that expected future payoffs are pinned down by traders' expectations of future prices: $\mathbb{E}_t[p_{t+1} + \delta d_{t+1}] = \mathbb{E}_t[p_{t+1}]$.

C.1 Dynamic Multipliers

We start by studying dynamic multipliers when traders either extrapolate one lag of past fundamentals or one lag of past prices.

C.1.1 Extrapolating Fundamentals

Suppose that traders believe that *flows* evolve according to:[31]

$$f_{t+1} = \theta_0 f_t + \theta_1 f_{t-1} + e_{t+1} \tag{65}$$

where $e_{t+1} \overset{\text{iid}}{\sim} N(0, \sigma_e^2)$, and θ_0, θ_1 parameterize extrapolative beliefs. This nests the rational benchmark when $\theta_0 = 1 - \phi_f$ and $\theta_1 = 0$. We continue to assume that $E_t[d_{t+1}] = 0$, so that expected future payoffs are pinned down by expectations of future prices.

We can then form expectations of future payoffs by iterating forward the market clearing condition and using (65):

$$E_t[p_{t+1}] = \left(\frac{\theta_0 + \frac{\kappa\theta_1}{\zeta}}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}} \right) f_t + \left(\frac{\theta_1}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}} \right) f_{t-1}. \tag{66}$$

We can then rewrite traders' demand curves as:

$$q_{it} = -\zeta p_t + \kappa \left[\left(\frac{\theta_0 + \frac{\kappa\theta_1}{\zeta}}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}} \right) f_t + \left(\frac{\theta_1}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}} \right) f_{t-1} \right] + f_{it}. \tag{67}$$

Market clearing then yields:

$$p_t = \left(\frac{1}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}} \right) f_t + \left(\frac{\kappa\theta_1/\zeta}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}} \right) f_{t-1}. \tag{68}$$

[31] We chose this expression to study extrapolation in the simplest possible setting that nested the rational expectations benchmark. This can easily be generalized, for example by including further lags.

The demand elasticity and the price multiplier can then be written as:

$$\text{Demand Elasticity}: \quad -\frac{\partial q_{it}}{\partial p_t} = \zeta \tag{69}$$

$$\text{Price Multiplier}: \quad \frac{\partial p_t}{\partial f_t} = \frac{1}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}} \tag{70}$$

$$\text{Dynamic Multiplier}: \quad \frac{\partial p_{t+h}}{\partial f_t} = (1-\phi_f)^{h-1}\left(\frac{1-\phi_f+\frac{\kappa\theta_1}{\zeta}}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}}\right). \tag{71}$$

These expressions allow us to highlight three points. First, as in the static case, extrapolating fundamentals affects the intercept but not the slope of agents' demand curves. This means that fundamental shocks may be amplified or dampened relative to the rational benchmark, but demand elasticities remain unchanged. Second, when $h \geq 1$, the multiplier remains decreasing in the horizon, and its dynamics reflect the persistence of fundamentals.[32] Third, the multiplier is increasing on impact if and only if $1-\phi_f+\frac{\kappa\theta_1}{\zeta} > 1 \implies \frac{\kappa\theta_1}{\zeta} > \phi_f$, i.e., when extrapolative beliefs are sufficiently strong to generate amplification through expectations.

Remark 1. *Under fundamental extrapolation, the dynamic multiplier eventually inherits the persistence of flows. When traders only extrapolate the most recent fundamental, the dynamic multiplier inherits the persistence of flows after the first lag.*

C.1.2 Extrapolating Past Prices

Suppose expectations are formed according to:[33]

$$\mathbb{E}_t[p_{t+1}] = \theta_{p,0}p_t + \theta_{p,1}p_{t-1} - \theta_{f,0}f_t, \qquad \theta_{p,1} < \theta_{p,0}. \tag{72}$$

[32] If investors extrapolate H lags of past fundamentals, the dynamic multiplier inherits the persistence of flows after H periods instead of 1.

[33] We chose this expression to study extrapolation in the simplest possible setting that nested the rational expectations benchmark. This easily be generalized, for example by including further lags.

We can then rewrite traders' demand curves as:

$$q_{it} = -(\zeta - \kappa\theta_{p,0})p_t + \kappa\theta_{p,1}p_{t-1} - \kappa\theta_{f,0}f_t + f_{it}. \tag{73}$$

Market clearing then yields:

$$p_t = \left(\frac{\kappa\theta_{p,1}}{\zeta - \kappa\theta_{p,0}}\right)p_{t-1} + \left(\frac{1-\kappa\theta_{f,0}}{\zeta - \kappa\theta_{p,0}}\right)f_t. \tag{74}$$

where as long as $\left(\frac{\kappa\theta_{p,1}}{\zeta-\kappa\theta_{p,0}}\right) < 1$, the process is stationary. The demand elasticity and the price multiplier can then be written as:

$$\text{Demand Elasticity :} \quad -\frac{\partial q_{it}}{\partial p_t} = \zeta - \kappa\theta_{p,0} \tag{75}$$

$$\text{Price Multiplier :} \quad \frac{\partial p_t}{\partial f_t} = \frac{1-\kappa\theta_{f,0}}{\zeta - \kappa\theta_{p,0}}. \tag{76}$$

We can then also solve for the dynamic multiplier as follows:

$$\frac{\partial p_{t+h}}{\partial f_t} = \left(\frac{1-\kappa\theta_{f,0}}{\zeta - \kappa\theta_{p,0}}\right)\left(\frac{(1-\phi_f)^{h+1} - \left(\frac{\kappa\theta_{p,1}}{\zeta-\kappa\theta_{p,0}}\right)^{h+1}}{(1-\phi_f) - \left(\frac{\kappa\theta_{p,1}}{\zeta-\kappa\theta_{p,0}}\right)}\right). \tag{77}$$

This expression illustrates how there are now two persistence parameters that govern dynamics: the persistence of fundamentals $(1-\phi_f)$, and the endogenous price persistence induced by extrapolation $\left(\frac{\kappa\theta_{p,1}}{\zeta-\kappa\theta_{p,0}}\right)$. When the sum of these terms is greater than one, the impulse response is hump-shaped. Even when fundamentals are weakly persistent, prices can display excess persistence purely due to the feedback effect between prices and beliefs that comes from learning from past prices.

Remark 2. *Extrapolating past prices introduces endogenous persistence beyond that of fundamentals. Dynamic multipliers can therefore exhibit hump-shaped dynamics that differ from the (in our case monotonic) dynamics of the underlying fundamentals.*

While the static price impact alone may not distinguish between different mechanisms, dynamics can be informative (Davis et al. 2026). If the persistence of dynamic multipliers does not match that of fundamentals, then extrapolative beliefs are likely at play.

C.2 Trading Behavior

Under rational expectations, investors either trade contrarian with respect to both short-run and long-run returns, or trade momentum with respect to both short-run and long-run returns. Instead, with extrapolative beliefs, investors can switch from being contrarian with respect to short-run returns to being momentum with respect to long-run returns.

To understand the properties of investors' trading behavior, we can look at how changes in holdings correlate with past returns at different horizons. We start by looking at the covariance of changes in holdings with respect to short-run returns, and then look at how this covariance differs once we consider how changes in holdings correlate with long-run returns instead.

C.2.1 Mislearning from Fundamentals

In this section we study the properties of investors' trading behavior when they extrapolate fundamentals.

Covariance with respect to short-run returns When investors mislearn from fundamentals as in (65), we can write reduced-form changes in individual demands in the following form:

$$\Delta q_{it} = -a\,\Delta p_t + c\,\Delta f_t + d\,\Delta f_{t-1} + \Delta f_{it}. \tag{78}$$

This nests the competitive equilibrium when $a = \zeta$, $d = 0$ and $c = \frac{\kappa(1-\phi_f)}{\zeta-\kappa(1-\phi_f)}$. Under the belief structure in (65), the coefficients are given by $c = \frac{\kappa\theta_0 + \frac{\kappa^2\theta_1}{\zeta}}{\zeta - \kappa\theta_0 - \frac{\kappa^2\theta_1}{\zeta}}$ and $d = \frac{\kappa\theta_1}{\zeta-\kappa\theta_0-\frac{\kappa^2\theta_1}{\zeta}}$.

Imposing market clearing yields equilibrium price changes:

$$\Delta p_t = \frac{c+1}{a}\Delta f_t + \frac{d}{a}\Delta f_{t-1}. \tag{79}$$

Substituting this expression back into individuals' demand functions lead to the following changes in equilibrium asset demands:

$$\Delta q_{it} = \Delta f_{it} - \Delta f_t. \tag{80}$$

Thus, as in the price-extrapolation case, equilibrium demand corresponds to investor i's own demand shock relative to the aggregate one.[34] The covariance between changes in investor i's holdings and short-run returns is therefore:

$$Cov(\Delta q_{it}, \Delta p_t) = Cov(\Delta f_{it}, \Delta p_t) - \frac{\sigma_e^2}{a}\left(\frac{2(c+1) - d\phi_f}{2 - \phi_f}\right). \tag{81}$$

To simplify this further, assume that individual flows load on aggregate flows according to:

$$\Delta f_{it} = \beta_i \Delta f_t + \varepsilon_{it}, \qquad Cov(\varepsilon_{it}, \Delta p_t) = 0. \tag{82}$$

Then (81) simplifies to:

$$Cov(\Delta q_{it}, \Delta p_t) = (\beta_i - 1)\frac{\sigma_e^2}{a}\left(\frac{2(c+1) - d\phi_f}{2 - \phi_f}\right). \tag{83}$$

Thus, whenever $\beta_i < 1$, meaning that investor i's flows move less than one-to-one with aggregate flows, the covariance is negative and investors appear contrarian with respect to short-run returns.

Covariance with respect to cumulative long-run returns Define the s-period cumulative return as:

$$p_t - p_{t-s} = \sum_{k=0}^{s-1} \Delta p_{t-k}. \tag{84}$$

[34]Notice that the equilibrium asset demand is different than the investors' demand function. Equilibrium asset demand is the quantity at the equilibrium price. An asset demand instead considers the hypothetical demand an agent would hold for any given price, including all off-equilibrium prices. While the equilibrium asset demand is the same under price and fundamental extrapolation, asset demands are very different in the two cases, leading to substantial differences in the resulting multipliers, and equilibrium price and trading dynamics.

Using the equilibrium price dynamics and the AR(1) structure of fundamentals yields:

$$Cov(\Delta q_{it}, p_t - p_{t-s}) = (\beta_i - 1)\frac{\sigma_e^2}{a(2-\phi_f)}\Big[(c+1)\Big(1+(1-\phi_f)^{s-1}\Big) - d\Big(1-(1-\phi_f)^s\Big)\Big]. \quad (85)$$

If $0 < d < c$, the bracketed term is positive for all s, so the sign of trading behavior is determined entirely by β_i. In particular, investors are contrarian with respect to both short-run and long-run returns when $\beta_i < 1$, while they are momentum traders at all horizons when $\beta_i > 1$.

Remark 3. *When individual flows correlate less than one-for-one with aggregate flows, fundamental extrapolation delivers trading behavior that is contrarian with respect to both short-run and long-run returns.*

C.2.2 Mislearning from Prices

In this section we study the properties of investors' trading behavior when they extrapolate prices.

Covariance with respect to short-run returns When investors learn from prices as in (72), changes in holdings and in equilibrium prices are given by:

$$\Delta p_t = \frac{b}{a}\Delta p_{t-1} + \frac{1+c}{a}\Delta f_t = \frac{1+c}{a}\sum_{j=0}^{\infty}\left(\frac{b}{a}\right)^j \Delta f_{t-j}, \qquad \left|\frac{b}{a}\right| < 1. \quad (86)$$

$$\Delta q_{it} = -a\,\Delta p_t + b\,\Delta p_{t-1} + c\Delta f_t + \Delta f_{it} = \Delta f_{it} - \Delta f_t \quad (87)$$

When traders learn information from prices as in the more general case considered in (72), the reduced-form coefficients are given by: $a = \zeta - \kappa\theta_{p,0}$, $b = \kappa\theta_{p,1}$, and $c = -\kappa\theta_{f,0}$. The REE is obtained in the limiting case $\theta_{p,0} = \frac{\zeta}{\kappa}$, $\theta_{p,1} = 0$, and $\theta_{f,0} = \frac{1}{\kappa}$, which implies $a = 0$, $b = 0$, and $c = -1$.[35]

[35] In this case, demand is perfectly inelastic and the recursion in (56) no longer applies.

The covariance between changes in investor i's holdings and price changes is therefore:

$$Cov(q_{it}, \Delta p_t) = Cov(\Delta f_{it}, \Delta p_t) - \frac{(1+c)\sigma_e^2}{a} \left(\frac{2 - \frac{b}{a}(2-\phi_f)}{(2-\phi_f)\left[1 - \frac{b}{a}(1-\phi_f)\right]} \right). \tag{88}$$

To simplify this further, we need to make assumptions as to how individual flows correlate with aggregate flows. Assume that:

$$\Delta f_{it} = \beta_i \Delta f_t + \varepsilon_{it}, \qquad Cov(\varepsilon_{it}, \Delta p_t) = 0. \tag{89}$$

Then (88) simplifies to:

$$Cov(q_{it}, \Delta p_t) = (\beta_i - 1)\frac{\sigma_e^2}{a} \left(\frac{2 - \frac{b}{a}(2-\phi_f)}{(2-\phi_f)\left[1 - \frac{b}{a}(1-\phi_f)\right]} \right). \tag{90}$$

As long as $\beta_i < 1$, meaning that individual flows move less than one-to-one with aggregate flows, then investors are contrarian with respect to short-run returns.

Covariance with respect to cumulative long-run returns. Define the s-period cumulative return as:

$$p_t - p_{t-s} = \sum_{k=0}^{s-1} \Delta p_{t-k}. \tag{91}$$

The covariance of changes in holdings with respect to long-run returns is then given by:

$$Cov(\Delta q_{it}, p_t - p_{t-s}) = (\beta_i - 1)\frac{\sigma_e^2}{a} \left(\frac{1 + (1-\phi_f)^{s-1} - \frac{b}{a}(2-\phi_f)}{(2-\phi_f)\left(1 - \frac{b}{a}(1-\phi_f)\right)} \right). \tag{92}$$

As long as $\frac{b}{a} > \frac{1}{1+(1-\phi_f)}$, there exists s, such that investors are momentum with respect to long-run returns. Equations (90) and (92) make clear that trading behavior across horizons is governed by the ratio $\frac{b}{a}$, which captures extrapolation from past prices, while the intercept term c only rescales price responses and therefore does not affect equilibrium trading behavior or whether investors appear contrarian or momentum traders.

Therefore, a key difference between price extrapolation and fundamental extrapolation lies in the pattern of trading behavior with respect to returns at different horizons. When investors extrapolate *prices*, price changes inherit an endogenous feedback component through lagged prices. This generates two competing forces: a scarcity effect (higher prices induce selling) and an informational effect (recent price increases raise expected future prices). The dependence on fundamentals through $\theta_{f,0}$ shifts the intercept of demand but does not affect this feedback mechanism. When extrapolative beliefs are strong enough, investors can appear contrarian with respect to short-run returns but momentum with respect to longer-run cumulative returns (Bastianello and Fontanier 2026). These patterns are consistent with empirical evidence, and can jointly explain trading behavior consistent with the disposition effect, and extrapolative demand (Jin and Peng 2026).

Under *fundamental extrapolation*, by contrast, prices are simply a linear filter of current and lagged fundamentals. There is no additional persistence created by price feedback. Consequently, the sign of the covariance between trading and returns is the same at all horizons: if investors are contrarian with respect to short-run returns, they are contrarian with respect to long-run returns as well, and similarly for momentum trading. Thus, horizon-dependent trading patterns can arise naturally under price extrapolation but not under fundamental extrapolation.

Remark 4. *When individual flows correlate less than one-for-one with aggregate flows, fundamental extrapolation delivers trading behavior that is contrarian with respect to both short-run and long-run returns. Instead, price extrapolation delivers trading behavior which is contrarian with respect to short-run returns, but momentum with respect to long-run returns.*

Only extrapolation from prices, through the ratio $\frac{b}{a}$, shapes trading behavior across horizons, whereas extrapolation from fundamentals shifts the intercept of demand and rescales price responses without altering whether investors appear contrarian or momentum traders.