Intermediaries and the Stock Market: A Structural Belief-Based Approach

Stefano Cassella* Huseyin Gulen† Marc Stam‡

March 26, 2026

Abstract

Intermediary asset-pricing theories predict that as households delegate investment decisions, professional investors play an increasingly important role in determining market valuations. Existing tests typically rely on indirect proxies for intermediary risk preferences or cross-asset comparisons that may confound intermediation with other forces. We propose a belief-based test in the U.S. stock market, where delegation has changed markedly over the past 60 years and investor beliefs are directly observed in surveys. We estimate a latent-state model in which a time-varying, unobserved influence weight maps retail and professional return expectations into market valuations, allowing us to recover a decades-long latent series of each group's influence. We find that households' influence has declined with delegation, but that retail investors remain considerably more influential than administrative measures of delegation would suggest. Variation in influence reflects both transitory shocks linked to risk and persistent shifts associated with major regulatory, social, and market-structure changes, which we identify using a large language model.

*Tilburg University; s.cassella@tilburguniversity.edu
†Purdue University; hgulen@purdue.edu
‡Tilburg University; m.h.a.stam@tilburguniversity.edu

1 Introduction

Recent work on market macrostructure examines how the organization of financial markets shapes asset-price dynamics (e.g., Haddad and Muir, 2025). In this growing literature, a key area investigates how rising intermediation and asset management influence price behavior (e.g., Scharfstein, 2018; Haddad and Muir, 2021; Ma et al., 2022; Duffie, 2022). Empirical studies in this area compare asset classes or countries with differing intermediation levels (e.g., Haddad and Muir, 2021; Baron and Muir, 2022), showing that banks' financial health,[1] a proxy for intermediaries' risk attitudes, predicts future returns more strongly in more intermediated markets.[2]

In this paper, we take a different approach to assessing whether intermediation matters for asset prices. First, we focus exclusively on a within-market analysis of the US stock market. This design avoids the unobserved heterogeneity that can arise in cross-country or cross-asset comparisons, while exploiting the substantial variation in US market intermediation from 1960 to the present (e.g., French, 2008; Stambaugh, 2014a). Second, we avoid preference-based tests of intermediary asset pricing. Because risk preferences are largely unobserved, such tests conflate the role of intermediaries with assumptions about risk, resulting in joint hypothesis problems (Bordalo et al., 2024b). What is more, the challenge of not being able to observe preferences directly is magnified in tests of intermediary-based theories, since distinguishing these theories from frictionless benchmarks (e.g., Santos and Veronesi, 2022) requires controlling for households' preferences, and these too are unobservable.

Instead, we take a novel behavioral perspective, as we examine whether the rising presence of intermediaries in the US stock market observed over the last 60 years amplifies the influence of these market participants' *beliefs* on asset prices, relative to the beliefs held by Households. Using beliefs in intermediary-asset pricing tests has several advantages. First, over the last decade, research in behavioral finance has documented how directly available survey-based measures of expectations are a meaningful gauge of investor beliefs (e.g., Greenwood and Shleifer, 2014; Giglio et al., 2021), and both theory and empirical work have developed to show how useful survey expectations are in reconciling several facts about financial markets (e.g., Barberis et al., 2015a; Jin and Sui, 2022; Nagel and Xu, 2022; Bordalo et al., 2024a). Second, survey data on the return expectations of different types of market participants is available, so that we can estimate the role of intermediaries' beliefs for asset prices while explicitly controlling for Households' expectations. We take stock of the maturity this field

[1] Banks here are broadly defined to include broker–dealers, commercial banks, and bank holding companies.

[2] An adjacent literature treats intermediaries' health as a cross-sectional pricing factor (e.g., He et al., 2017; Adrian et al., 2014).

has reached, and perform novel belief-based tests on the role of intermediaries in the stock market.

We begin our analysis by estimating a novel structural model of aggregate asset prices that allows us to recover the time-varying influence of intermediaries and households in the US stock market. Specifically, we set up a present-value model in which, in addition to the traditional discount-rate drivers, the price-dividend ratio of the market also reflects a weighted sum of the expectations held by professionals and retail investors. We treat the weighting scheme combining retail and professional expectations as a latent time-series, which we recover via Kalman-filtering techniques. This weight captures the relative influence of each investor type's beliefs on aggregate market valuation.

We find it useful to compare our latent-variable approach with past research relying on Flow-of-Funds measures to gauge households' and intermediaries' influence in the stock market. These measures based on administrative data use the size of households' direct versus indirect (i.e., intermediated) ownership of stocks to gauge qualitatively the relative importance of households for asset prices. At the same time, there are both conceptual and econometric hurdles to inferring households' and intermediaries' importance in this way. From a conceptual standpoint, this approach does not test, but rather assumes that intermediaries play an increasing role due to rising delegation. This is an important limitation: even though households hold stocks indirectly (i.e., via intermediaries) more and more over time, whether this leads to a specific role played by the intermediaries themselves depends on the contracting and monitoring frictions underlying the delegation process (e.g., He and Krishnamurthy, 2018), and these can change over time (e.g., Rogerson, 1985; Spear and Srivastava, 1987). What is more, skeptics of the intermediary asset-pricing paradigm point out that to the extent that households adjust their portfolios based on professionals' actions, households are still the only important market participant even in a deeply intermediated market. Administrative data also faces a measurement challenge, in that accounts such as the Federal Reserve Flow of Funds in the US, treat the Household sector as a residual category, leading at best to a noisy measurement of households' delegation of financial decisions to professionals. All in all, instead of assuming that households' influence on aggregate asset prices is observable, we treat it as a latent process featuring both a stochastic-trend component capturing permanent shocks, as well as a cyclical component isolating more transitory variation in the relative influence of Households over professional investors.

Our estimation, based on data spanning over 60 years, delivers three key takeaways. First, the influence of households' beliefs on asset prices has declined considerably over time. At the beginning of our sample, the weight on households' expectations is statistically indistinguishable from one for much of the 1960s; by 2023, it falls to about 50%. From

a statistical standpoint, we can reject the null of no-influence of intermediaries in favor of the intermediary-asset pricing alternative of a positive influence for a fraction of 90% of our sample. Second, though both our estimates and Flow-of-Funds data on Households' direct versus indirect (intermediated) ownership deliver the same qualitative message about households' influence slowly subsiding over time, the two differ quantitatively. In particular, our structural estimates of households' and intermediaries' influence are on average twice as large as what would be implied by administrative data. This result suggests that, while the delegation of financial decisions to professional investors has strengthened the influence of these investors' beliefs on asset prices, households as principals can still influence professional decisions ex-ante via contracting and ex-post via rebalancing and asset reallocation. As a result, contrary to the stark view about delegation that previous work has taken (e.g., Stambaugh, 2014b), our results indicate that a more nuanced view about the impact of the delegation process of financial markets may be warranted. Third, a belief-based sentiment index that incorporates our time-varying weights strongly predicts future stock returns, a result that addresses the puzzlingly weak link between survey expectations and returns documented in prior work (e.g., Greenwood and Shleifer, 2014).

These insights are robust to several alternative specifications, in which: (i) we include in our present-value model explicit controls for observable risk-aversion measures proposed in past work (e.g., Campbell and Cochrane, 1999; He et al., 2017); (ii) we explicitly account for unobservable variation in risk premia, in the spirit of earlier work (e.g., Cochrane, 2011); (iii) we adjust stock market valuation for structural breaks (Lettau and Van Nieuwerburgh, 2008); (iv) we include or not a deterministic trend component in our model of the latent process governing investors' influence.

In the second part of the paper, we seek to shed light on the origins of the fluctuations in retail investors' and professional investors' influence in the stock market. We hypothesize that transitory shocks to investors' influence on the market can be traced back to variation in risk and risk preferences, variation in the financial constraints households face, and variation in attention. We find evidence that retail investors' influence rises when households become more risk tolerant, while it declines in recessions or following a period of high stock-market volatility. Our results also show that households' influence rises with households' debt-to-income and when a larger share of the population is employed. This is consistent with a view in which leverage as well as income loosen households' financial constraints (Santos and Veronesi, 2022). We instead do not find much evidence in favor of attention playing a role.

Next, we seek to reconcile the stochastic-trend component of our recovered time-series of investor influence. This component reflects permanent shocks, which we conjecture stem from major changes in the technology and the rules and regulations that retail investors and

professional intermediaries face when trading in the US stock market. To test our conjecture, we identify with the support of a large-language model (LLM) roughly 80 major events in recent US history that affect retail investors, professional investors, or both. We then classify these events, both manually and using an LLM with reasoning capabilities, as either positive shocks to households' influence in the stock market (e.g., regulation reducing barriers to entry or trading costs for retail investors, or the rise of social finance platforms), or positive shocks to intermediaries (e.g., regulation allowing banks to derive a large fraction of their revenue from securities trading, or regulation institutionalizing mutual fund advertising). In predictive regressions, we are able to show that positive shocks to households' influence (professional investors' influence) indeed lead to subsequent lower influence of professional (lower influence for households). Taken together, this analysis allows us to reconcile the novel variation in investors' influence that we measure, with economic intuition and historical events.

Having established that the relative influence of retail and professional investors varies substantially over time, we next examine the implications of this finding for tests linking survey expectations to future returns. Specifically, we rely on insights from intermediary asset pricing to perform new tests of behavioral finance theories. This literature shows that return expectations are theoretically important (e.g., Barberis et al., 2015a; Jin and Sui, 2022). Yet, the empirical evidence of a role of these expectations for asset prices is more modest. In discussing seminal work on survey expectations of returns by Greenwood and Shleifer (2014), Shleifer (2019) notes that survey-based measures of investor beliefs about future returns have little predictive power for future market returns.[3] Importantly, this potentially negative assessment could result from empirical work that has so far neglected the broad patterns of delegation and changes in investor influence which we have documented earlier in the paper. Thus, we revisit the existing empirical tests linking return expectations to predictability under an intermediary asset pricing view.

To that end, we first replicate over our 63-year long sample period the evidence in prior work that individual return expectations from either retail investors or professionals do not predict future stock returns strongly. We then form an index of beliefs from surveys, which we refer to as belief-based sentiment (henceforth BBS). The index incorporates the notion of time-varying influence of retail investors and professional investors that is inspired by intermediary-asset pricing. We form alternative versions of BBS that are obtained using

[3]In a column prepared for the National Bureau of Economic Research, Andrei Shleifer summarizes results from his recent work with Greenwood on survey expectations and states "Is such extrapolation an effective return forecasting strategy? The answer is no. The correlation between the Gallup expected returns and the S&P [...] is negative, although statistically insignificant". See the entire article at the following link: https://www.nber.org/reporter/2019number1/return-survey-expectations.

either the time-series of investor weights that we recover using our structural model, or the administrative time-series of direct ownership of stocks by the Household sector released by the Federal Reserve. We show that accounting for the time-varying influence of different investor types allows us to detect much stronger predictability of stock returns by investor return expectations. The predictability of future market returns further improves when we replace our baseline index BBS with its irrational component, which is constructed based on machine-learning predictions of future returns.

This paper contributes to the literature on intermediation and asset prices. A growing body of work argues that intermediaries can have first-order effects on prices because the information frictions, regulation, and incentives that they face differ from those faced by households (Basak and Pavlova, 2013, He and Krishnamurthy, 2013, He et al., 2017, Adrian et al., 2014, Haddad and Muir, 2021). Skeptics instead emphasize a frictionless view: contracts align households' objectives with intermediaries ex ante, and households can dynamically adjust their portfolios ex post, "undoing" any intermediary-driven wedge between equilibrium prices and those justified by households' risk preferences (Cochrane, 2011). Skeptics also point out that much empirical work proxies for intermediaries' role using their financial constraints, with recent theory arguing that these constraints may very well originate in the household sector (Santos and Veronesi, 2022). Ultimately, the empirical challenge this literature faces is to link price variation to intermediaries while explicitly accounting for households. We propose doing so via beliefs rather than preferences or constraints, since beliefs are measurable for broad investor groups in surveys. We develop a structural model and latent-variable valuation approach that estimates the time-varying influence of intermediaries' beliefs in the US stock market, a setting prior work often avoids because households are directly present. By controlling for household beliefs, we provide cleaner tests on the role of intermediaries in the market. Our results support intermediary-based theories, while showing households retain substantial average influence. We also document cyclical and secular shifts in intermediaries' influence, and connect them to transitory forces (e.g., business-cycle conditions) and permanent changes (e.g., regulation) in market macrostructure.

Our second contribution is to the literature on biased beliefs in asset markets.[4] Directly related, Greenwood and Shleifer (2014) use survey data on return expectations to show that investors' expectations systematically deviate from rational expectations. Their evidence that biased return beliefs influence asset prices is mixed. We argue this is because existing tests overlook households' delegation of portfolio decisions to professionals, which shifts whose expectations are relevant in equilibrium. Incorporating this shift into a new metric

[4]See Muth (1961), La Porta (1996), Barberis et al. (2015b), Barberis et al. (2018), Bordalo et al. (2018), Bordalo et al. (2019), Nagel and Xu (2022).

of biased return expectations, our BBS index, we find a strong negative relation between marketwide bias and subsequent returns, consistent with behavioral theories. Our paper is also related to work on belief heterogeneity, such as McCarthy and Hillenbrand (2025). They study heterogeneity in biases, not the time-varying importance of investor types implied by delegation. Cassella and Gulen (2018) and Da et al. (2021) emphasize extrapolative expectations (and their time-series variation), whereas we use return expectations more broadly to study how delegation affects whose beliefs matter over time. Finally, Bordalo et al. (2024a) analyze how cash-flow beliefs shape aggregate and cross-sectional prices, while abstracting from the expectations of returns and the dichotomy between retail and professional investors which are at the center of our paper.

Third, we contribute to the literature on measuring equity market sentiment.[5] This literature has largely relied on a *top-down* approach, inferring sentiment from market outcomes.[6] While flexible, this approach raises interpretation challenges, since market outcomes reflect not only beliefs, but also preferences. Moreover, traditional sentiment measures leave unclear whose beliefs are being measured, and what component of these measures reflects irrational beliefs. This limits the use of these measures to study delegation, or to shed light on the role of biases in beliefs for asset prices. We propose a *bottom-up* alternative based on direct measures of investor expectations. By combining the beliefs of households and professional investors based on our newly measured time-series of investor influence, we construct a sentiment index that is robust to shifts in the representative investor. Moreover, our belief-based sentiment measure can be easily benchmarked against model-implied rational beliefs, allowing us to identify belief-based expectations and provide sharper tests of behavioral asset-pricing theories.

2 A Structural Model of Market Valuation

2.1 Setup and Null Hypothesis of No Role for Intermediaries

A traditional view in finance is that market valuations vary with changes in investors' risk appetite, that is, discount-rate variation, and with changes in expected dividend growth (Campbell and Shiller, 1988). Our empirical framework builds on recent theoretical and empirical work in behavioral finance showing that fluctuations in prices can also be understood through variation in investors' subjective expectations of future returns (e.g., Barberis et al.,

[5] See for instance Lee et al. (1991), Neal and Wheatley (1998), Qiu and Welch (2006), Baker and Wurgler (2006), M. Baker and Wurgler (2007), Da et al. (2015).

[6] Recent applications study anomalies (Stambaugh et al., 2012), international market comovement (M. P. Baker et al., 2012), and the mean–variance relation (Yu and Yuan, 2011).

2015a, 2018).

We combine this insight with recent work in intermediary asset pricing. This literature argues that the relative importance of different investor types for price determination depends on the extent to which households delegate financial decisions to intermediaries. In a fully non-intermediated market, or in a market in which agency conflicts between households as principals and intermediaries as agents can be contracted away, only households matter for prices. The same is true if households can promptly adjust their asset demand so as to undo any undesired influence of professional trading on their portfolios. By contrast, in a deeply intermediated market, where households' direct ownership is constrained and rapid portfolio adjustment is unlikely, or in a market with severe agency frictions, intermediary asset-pricing theories imply that intermediaries and institutional investors contribute disproportionately to price determination.

Our empirical framework is motivated by the idea that, although households delegate financial decisions to professionals, it remains unclear to what extent such delegation in the US stock market corresponds to the frictionless benchmark in which professionals do not matter for prices. To shed light on this issue, we draw on the behavioral-finance insight that asset valuations are linked to investors' subjective beliefs. Specifically, we estimate the following structural model of the market dividend–price ratio:

$$\begin{aligned} D/P_t &= \beta EXP_t + \Gamma' X_t + \varepsilon_t \\ &= \beta \left[w_t EXP_t^{RI} + (1 - w_t) EXP_t^{PRO} \right] + \Gamma' X_t + \varepsilon_t. \end{aligned} \tag{1}$$

As in earlier work in behavioral finance, aggregate market valuation, represented by the log dividend–price ratio of the market, comoves with investors' subjective return expectations. Unlike that literature, however, our econometric specification incorporates the central insight of intermediary asset pricing by allowing the influence of professional investors' expectations, EXP_t^{PRO}, and households' expectations, EXP_t^{RI}, on aggregate price formation to differ and to vary over time.

In the standard Campbell and Shiller (1988) log-linear representation, the dividend–price ratio is driven by an infinite sum of expectations of future returns and future cash-flow growth. In the main analysis, we abstract from cash-flow growth expectations because prior work shows that they explain little of the variation in the aggregate dividend–price ratio (e.g., Cochrane, 2011). Moreover, under the standard assumption that expected returns are autoregressive, the infinite sum of future expected returns is proportional to current one-period-ahead expected returns, which provides a rationale for expressing the dividend–

price ratio as a compact function of the next-period return expectations.[7] Equation (1) also includes a vector of control variables, X_t, observed or unobserved, which we incorporate for consistency with earlier work on the determinants of aggregate valuations.

While the model permits heterogeneity in beliefs across the two broad investor groups described above, it abstracts from heterogeneity within each group. Different types of retail investors may form expectations differently and may affect asset prices to different degrees. Likewise, the category of professional intermediaries includes many different types of institutional investors such as pension funds, mutual funds, hedge funds, and banks operating proprietary trading desks. Importantly, estimating Equation (1) does not require observing the expectations of each investor subtype separately. What is required instead is the availability of two expectation time series that capture variation in beliefs that is common among different types of investors within each broad investor category. We later show that the main empirical proxies for investor expectations used in the paper are consistent with this condition.

In principle, our approach to identifying the time-varying influence of retail and professional investors need not rely on subjective return expectations. An alternative would be to base the analysis on subjective cash-flow expectations, which have in some work been argued to be more tightly connected to valuations than return expectations (e.g., Nagel and Xu, 2022). In practice, however, we are not aware of long-running cash-flow expectation series for both retail investors and professionals, making that route difficult to pursue. A second alternative would be to study the impact of these two broad groups of investors by relating variation in their risk aversion to valuations. Here too, data limitations are substantial. First, available measures of retail risk aversion are mostly theory-based rather than empirical, leading to the question of how closely they resemble actual risk appetite. Second, empirical measures for professionals do exist, but they typically capture only a limited subset of intermediaries, such as banks. By contrast, return expectation series are available for both retail and sophisticated investors over long horizons, making them the most practical basis for our empirical analysis.

[7] To see this, suppress cash-flow-growth terms and let $x_t \equiv E_t^S[r_{t+1}]$ denote the de-meaned subjective expectation of next period's return. In the Campbell–Shiller log-linearization, the log dividend–price ratio loads on the discounted sum $\sum_{j=0}^{\infty} \kappa^j E_t^S[r_{t+j+1}]$, where $\kappa \in (0,1)$ is the log-linearization constant. If expected returns follow an AR(1), so that $E_t^S[r_{t+j+1}] = \rho^j x_t$, then

$$\sum_{j=0}^{\infty} \kappa^j E_t^S[r_{t+j+1}] = x_t \sum_{j=0}^{\infty} (\kappa\rho)^j = \frac{1}{1-\kappa\rho} x_t,$$

provided $|\kappa\rho| < 1$. Hence, next-period return expectations are a sufficient statistic for the component of the dividend–price ratio driven by expected returns.

Our main object of interest is the time-varying weight w_t. The traditional view that intermediaries have no role on asset prices maintains that $w_t = 1\ \forall t$, i.e., only households' influence market valuation. The more nuanced view of intermediary asset pricing is that w_t is subject to fluctuations and changes over time. A higher value of w_t corresponds to a greater loading of valuations on households' expectations, whereas a lower value implies a greater loading of the dividend-price ratio of the market on professional investors and financial intermediaries. Allowing this weight to vary over time enables the model to capture changes in the relative importance of households and professionals that may arise from secular shifts in delegation, agency frictions, or regulation. in the remainder of the paper we will refer to w_t as "households' influence" on asset prices. This labeling is purely for expositional purposes, as we do not seek to identify a causal relation between beliefs and aggregate valuation. Yet,in later tests we will connect w_t both to business-cycle variation in households' participation and propensity to hold US equities, and to shocks to the functioning of financial markets (e.g., regulatory innovations), that are likely to alter Households' influence for price formation.

Treating w_t as a latent state in Equation (1), our empirical objectives are twofold: first, to recover estimates of this latent process using a Kalman-filtering approach, and conduct hypothesis testing concerning the null of no-intermediary influence; and second, to relate the resulting time-series variation in the relative influence of households and intermediaries to its underlying economic drivers.

2.2 Model Architecture

To bring the model above to the data, we adopt a Kalman-filtering approach (Kalman, 1960). For consistency with prior work, all observable quantities are demeaned and expressed in logs. The model features one measurement equation and two latent processes, w_t and μ_t, which capture the time-varying influence of retail investor beliefs on asset prices and variation in an unobservable persistent discount-rate component, respectively:

$$dp_t = \beta\left[w_t\, EXP_t^{RI} + (1 - w_t)\, EXP_t^{PRO}\right] + \beta_\mu \mu_t + \varepsilon_t \qquad \varepsilon_t \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma_\varepsilon^2) \tag{2}$$

$$w_t = w_0 + \tau_t + u_t \tag{3}$$

$$\tau_t = \tau_{t-1} + \gamma + \zeta_t \qquad \zeta_t \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma_\zeta^2)$$

$$u_t = \phi u_{t-1} + \eta_t \qquad \eta_t \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma_\eta^2)$$

$$\mu_t = \rho \mu_{t-1} + \xi_t \qquad \xi_t \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma_\xi^2) \tag{4}$$

In our structural model, the latent weight w_t, which captures the relative influence of households compared with professional investors, follows a standard *trend-plus-cycle* specification commonly used in macroeconomics (Clark, 1987; Harvey, 1990; Harvey and Jaeger, 1993; Kuttner, 1994). The cyclical component u_t captures transitory fluctuations in household influence, for instance fluctuations associated with changes in broad economic conditions over the business cycle. Such temporary movements may arise from variation in factors that moderate the link between households' expectations and stock demand, including time-varying risk aversion (Campbell and Cochrane, 1999), financial frictions, and changes in attention induced by market conditions (Da et al., 2011; Karlsson et al., 2009).

The component τ_t instead captures long-lived and potentially permanent shifts in household influence in financial markets. Such shifts may arise, for instance, from regulatory or legal reforms that durably increase the role of professional investing, or from developments that permanently alter retail investors' direct participation in the stock market.[8]

We allow τ_t to include a deterministic trend component with slope γ. This parameter provides a direct way to test the conjecture that household influence on asset prices has declined over the last sixty years, possibly because of a gradual rise in delegation (French, 2008; Stambaugh, 2014b). Under that view, one would expect $\gamma < 0$. By contrast, under the frictionless benchmark discussed above, delegation does not alter whose beliefs matter for prices, implying $\gamma = 0$ (Cochrane, 2011; Santos and Veronesi, 2022). These competing views therefore map directly into the estimate of γ.[9]

The intercept w_0 captures the influence of retail investors at the beginning of the sample in 1963. Together, $w_0 = 1$ and $\gamma = 0$ correspond to the frictionless benchmark in which households fully determine prices and growing delegation does not diminish their influence over time. More generally, the estimated path of w_t allows us to quantify how closely the data align with benchmark of institutions' irrelevance at each point in recent US history.

In addition, following Cochrane (2011), we include a latent discount-rate component μ_t in Equation (2). We model this component as an AR(1) process to capture persistent variation in valuations that is not absorbed by investor expectations alone. This helps account for persistence in the dividend–price ratio that is difficult to reconcile using return-expectation dynamics alone (e.g., Nagel and Xu, 2022). We abstract instead for simplicity from modeling a separate latent process for expected dividend growth, in line with prior work showing that

[8] Later, in Section 5.2, we explicitly relate major events in the regulatory, competitive, and social evolution of the US stock market to variation in τ_t.

[9] As we later show in simulations in Section 6, our econometric approach does not mechanically generate a negative trend. If the null of no intermediary influence were true in the data, the model would recover a stable path for w_t fluctuating around one. The model can therefore provide a data-driven assessment of whether household influence in the US stock market has in fact eroded over time.

movements in the dividend–price ratio are not primarily driven by rational expectations of dividend growth.

In the next section, we provide a detailed discussion of the state-space representation and the assumptions underlying estimation.

2.3 Model Estimation

To estimate the model, we first rewrite the measurement equation in compact form as

$$\dot{dp}_t = \dot{H}_t x_t + \varepsilon_t, \tag{5}$$

where

$$\begin{aligned}
\dot{dp}_t &= dp_t - \beta EXP_t^{PRO} - H_t w_0, \\
\dot{H}_t &= \begin{bmatrix} H_t & H_t & 1 \end{bmatrix}, \\
H_t &= \beta \left(EXP_t^{RI} - EXP_t^{PRO} \right),
\end{aligned}$$

and

$$x_t = \begin{bmatrix} \tau_t \\ u_t \\ \mu_t \end{bmatrix}.$$

The measurement disturbance is assumed to satisfy

$$\varepsilon_t \overset{\text{iid}}{\sim} \mathcal{N}(0, R), \qquad R = \sigma_\varepsilon^2. \tag{6}$$

Following the structure of the model, we write the transition equation as

$$x_t = F x_{t-1} + c + G\Sigma_t. \tag{7}$$

Here,

$$F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \phi & 0 \\ 0 & 0 & \rho \end{bmatrix}, \qquad c = \begin{bmatrix} \gamma \\ 0 \\ 0 \end{bmatrix},$$

$$G = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \qquad \Sigma_t = \begin{bmatrix} \zeta_t \\ \eta_t \\ \xi_t \end{bmatrix},$$

with

$$\Sigma_t \overset{\text{iid}}{\sim} \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, Q \right), \qquad Q = \begin{bmatrix} \sigma_\zeta^2 & 0 & 0 \\ 0 & \sigma_\eta^2 & 0 \\ 0 & 0 & \sigma_\xi^2 \end{bmatrix}. \tag{8}$$

The latent state vector x_t contains the unobserved components that we seek to recover

from the data. The first two elements, τ_t and u_t, represent the permanent and transitory components of retail investors' influence, respectively. The third element, μ_t, captures the persistent discount-rate component. The matrices Q and R therefore govern the signal-to-noise ratio of the state-space system.[10]

in the estimation, for tractability we set $\beta_\mu = 1$ and calibrate the variance of the innovations of μ_t to absorb any scaling difference between the underlying discount rate process and the dividend–price ratio.[11]

The full vector of model parameters,

$$\theta = \left[\beta, w_0, \gamma, \phi, \rho, \sigma_\varepsilon^2, \sigma_\zeta^2, \sigma_\eta^2, \sigma_\xi^2\right] = \left[\theta_p, \theta_V\right].$$

Here, $\theta_V = \left[\sigma_\varepsilon^2, \sigma_\zeta^2, \sigma_\eta^2, \sigma_\xi^2\right]$ denotes the variance parameters, and $\theta_p = [\beta, w_0, \gamma, \phi, \rho]$ the remaining structural parameters. We estimate the model by maximum likelihood using the Kalman filter, which requires initial values for the latent states, an initial covariance matrix, and starting values for the parameters. Table 4 reports all initialization choices, their numerical values, and the rationale for them. In equations 3 and 4, σ_ζ^2 and σ_ξ^2 are treated as fixed and known to the econometrician. We calibrate σ_ξ^2 using prior estimates of the discount-rate process (Van Binsbergen and Koijen, 2010). We choose σ_ζ^2 so that the stochastic trend component of w_t can span the economically meaningful interval $[0, 1]$, where 0 and 1 correspond to the polar cases in which valuations are driven entirely by professional or retail expectations. At the same time, high values of σ_ζ^2 increase the likelihood that the recovered w_t is estimated outside that interval for extended periods. To preserve the linear state-space structure required by the Kalman filter, we do not impose the unit-interval restriction through a nonlinear transformation of w_t, such as a logit, or through explicit parameter constraints in estimation. Instead, we calibrate σ_ζ^2 to strike a balance between allowing sufficient flexibility in the stochastic-trend component of w_t and limiting economically implausible excursions outside $[0, 1]$.

To initialize the remaining variance parameters, σ_ε^2 and σ_η^2, for which we cannot readily obtain meaningful data-driven guesses, we are mindful of a practical challenge in trend–cycle state-space models, namely that different choices of the variance parameters imply different signal-to-noise ratios and can therefore generate different decompositions of the observed series into permanent and transitory components.[12] Therefore, to reduce dependence on

[10] In the baseline specification, we do not allow for covariance across shocks in the state vector, and innovations to the latent states are assumed to be orthogonal to the measurement disturbance in dp_t.

[11] To see that this normalization is without loss of generality, suppose the true discount-rate process is $\mu_t^* = \phi\mu_{t-1}^* + \epsilon_t^*$ with $Var(\epsilon_t^*) = \sigma^2$ and a loading of β_μ on the dp ratio. Defining the scaled process $\mu_t = \beta_\mu \mu_t^*$ implies $\mu_t = \phi\mu_{t-1} + \xi_t$, where $\xi_t = \beta_\mu \epsilon_t^*$ and thus $Var(\xi_t) = \beta_\mu^2 \sigma^2$. Hence, if the log dividend–price ratio loads on μ_t^* with coefficient β_μ, it loads on μ_t with coefficient 1.

[12] This concern is well grounded in the trend–cycle literature. See, for instance, Canova (1998), Harvey

any single variance calibration, we entertain a set of plausible diagonal (Q, R) specifications and estimate the model separately under each of them. For each candidate specification, indexed by $m = 1, \ldots, M$, we take the variance vector $\theta_V^{(m)}$ as given and estimate the remaining parameters by maximum likelihood. This yields a fitted solution consisting of the conditional parameter estimate $\widehat{\theta}_p^{(m)}$ and a recovered path $\widehat{w}_t^{(m)}$.

We then rank these fitted solutions using the negative log-likelihood and construct rank-weighted estimates by averaging across solutions. Letting ω_m denote the rank-based weight assigned to specification m, with $\sum_{m=1}^{M} \omega_m = 1$, our final reported parameter estimates are

$$\widehat{\theta} = \sum_{m=1}^{M} \omega_m \widehat{\theta}^{(m)},$$

where each $\widehat{\theta}^{(m)}$ combines the fixed variance vector $\theta_V^{(m)}$ with the estimated parameter vector $\widehat{\theta}_p^{(m)}$. The final recovered weight series is

$$\widehat{w}_t = \sum_{m=1}^{M} \omega_m \widehat{w}_t^{(m)}.$$

This procedure can be interpreted as a rank-weighted model-averaging approach over alternative variance specifications. Its purpose is not to impose a single preferred signal-to-noise ratio ex ante, but rather to let the final estimates reflect the relative fit of a range of plausible variance configurations while remaining less sensitive to any one particular choice of diagonal Q and R[13]. Appendix A.2 provides a detailed description of the candidate variance specifications, the ranking rule, and the weighting scheme.

Finally, to construct confidence intervals for both the estimated model parameters and the recovered time series of weights, we implement a residual bootstrap procedure. Specifically, we rely on the stationary block bootstrap of Politis and Romano (1994), adapted to a state-space setting with latent components and potentially serially correlated shocks. Details of the bootstrap procedure are provided in Appendix A.3.

3 Data

Several sources of data are needed to perform our analysis. First and foremost, we need long running time-series data on the expectations of retail investors and professional investors,

and Jaeger (1993), Morley et al. (2003), Nelson (1988).

[13]Appropriate selection of noise covariances Q and R is a widely recognized difficulty in the domain of state-space filtering. To alleviate the concern that our results are driven by a fixed and manual calibration of these parameters, we allow for variability by searching over a broad range of different pairs (a method used in computer science and engineering applications, see e.g., Ahmadi et al., 2025; Coskun et al., 2017). Conceptually, our method of performing a grid search and combining models based on the likelihood scores is closest to what is commonly labeled as a Bayesian approach (in e.g., Matisko and Havlena, 2013)

who we take to represent households and intermediaries in the stock market. Second, we need valuation and return data for the market, as well as a broader dataset of stock-market return predictors, which can be used to construct ex-ante measures of biases in beliefs. Third, we need to tap into administrative data and several additional sources, to collect data on households' direct ownership of stocks, which we can then compare to our estimates of retail investors' influence in the market. Other data sources, such as data on investor flows and portfolios, or market and country demographics, are also used in some of our tests. For parsimony, here we concentrate on the main data sources, and postpone a discussion of these additional data to the relevant section.

3.1 Investor Beliefs

Retail Investors

To measure retail investors' return expectations, our primary data source is the Gallup survey of investor optimism. The survey is well suited for our purposes because it is designed to capture the beliefs of the US population of retail investors. Since 1996, Gallup has collected expectations of returns from a monthly cross-section of approximately 1,000 individuals, focusing on those individuals with at least $10,000 invested in financial assets. Relative to other surveys of retail investor beliefs—such as the American Association of Individual Investors (AAII)—Gallup ensures coverage of actual stock market participants and is broadly representative of the average US retail investor. Moreover, unlike AAII, Gallup provides cross-sectional data on investor beliefs.[14] This feature is essential for constructing a long time series of retail-investor beliefs, as we explain below.

While Gallup provides direct measures of consensus expectations from 1996 to 2015, our objective is to construct a longer time series of aggregate retail-investor beliefs in order to study the impact of delegation on financial markets over the past sixty years. To do so, we: (i) use the Gallup data to infer how different types of households form expectations; and (ii) combine these estimated belief-formation rules with historical price data and households' stock market participation statistics to construct a long time-series of household-sector beliefs that aggregates heterogeneous expectations of different types of retail investors based on actual equity market participation.

The first step uses Gallup data to estimate belief formation across types of retail investors, defined based on demographic characteristics. Following a large literature, we assume that investor expectations are shaped by the extrapolation of past stock returns, with greater

[14]Other studies that rely on the Gallup survey data are Vissing-Jorgensen (2003), Kahneman and Deaton (2010), and Greenwood and Shleifer (2014).

weight placed on recent returns (e.g., Vissing-Jorgensen, 2003; Greenwood and Shleifer, 2014). We allow the sensitivity to past returns to vary across investor types, reflecting documented heterogeneity in the use of past information. For example, Malmendier and Nagel (2011) link differences in risk-taking behavior to investors' lifetime experiences, implying age-related heterogeneity in expectations. Such variation is also consistent with evidence from psychology on memory, accessibility, and heuristics (Higgins, 1996; Kahneman, Frederick, et al., 2002; Kahneman, 2003). Accordingly, we estimate return-extrapolation models separately for retail investors in different age brackets. To that end, we use quantitative data on retail investors' expectations collected by Gallup between January 2001 and April 2003, and estimate the following return extrapolation model for five age groups, each 10 years wide, between the ages of 25 and 75:[15]

$$\begin{aligned} \text{EXP}_{gt}^{RI} &= a_g + b_g \sum_{j=1}^{15} w_{gj} R_{(t-j+1)} + \epsilon_{gt} \\ w_{gj} &= \frac{(\lambda_g)^{(j-1)}}{\sum_{k=1}^{15} (\lambda_g)^{(k-1)}} \ , \end{aligned} \tag{9}$$

where EXP_{gt}^{RI} refers to an age group's consensus expectations as of time t, and R_{t-j} is the stock market return realized in year $t-j$. The results of this estimation, reported in Table 1 highlight heterogeneity in belief formation across age groups. Expectations for all age groups rise following good returns, and this is consistent with past work documenting return extrapolation. At the same time, differences in the relative influence of recent versus distant returns exist that are consistent with younger investors being more influenced by recent returns than older investors are. In addition, younger investors also display more optimistic expectations on average.

Taking stock of the heterogeneity documented above, the second step of our approach consists of using the in-sample parameter estimates for each age group ($\widehat{a_g}$, $\widehat{b_g}$, $\widehat{\lambda_g}$) to construct the time-series of retail investors' expectations EXP_t^{RI}:

[15] Quantitative data from Gallup is available as early as 1998, but prior to 2000, survey responses are winsorized at 0 (e.g., Vissing-Jorgensen, 2003). We avoid the distorting effect of such winsorization by concentrating on the 2000-2003 sample. Following Malmendier and Nagel (2011), we use survey weights and exclude individuals younger than 25 or older than 75.

$$
\begin{aligned}
EXP_t^{RI} &= \overline{a_t} + \overline{b_t} \sum_{j=1}^{15} w_j R_{t-j+1} \\
w_j &= \frac{(\overline{\lambda_t})^{(j-1)}}{\sum_{k=1}^{15} (\overline{\lambda_t})^{(k-1)}} \quad , \\
\overline{a_t} = \frac{\sum_{g=1}^{5} \widehat{a_g} DH_{g(t-1)}}{\sum_{k=1}^{5} DH_{k(t-1)}}, &\quad \overline{b_t} = \frac{\sum_{g=1}^{5} \widehat{b_g} DH_{g(t-1)}}{\sum_{k=1}^{5} DH_{k(t-1)}}, \quad \overline{\lambda_t} = \frac{\sum_{g=1}^{5} \widehat{\lambda}_g DH_{g(t-1)}}{\sum_{k=1}^{5} DH_{k(t-1)}}
\end{aligned}
\tag{10}
$$

In line with the survey evidence, the model of consensus belief by households that we adopt posits that the extrapolation of past returns is an important driver of aggregate retail-investor beliefs. The model allows for time-varying parameters in the aggregation, which reflect time-series variation in the relative prevalence of each age group. We proxy for such prevalence by means of the direct holdings (DH) of public US equities by households whose head belongs to a given group g:

$$
DH_{gt} = N_{gt}^{HH} \pi^D{}_{gt} \overline{DH_{gt}} \tag{11}
$$

In words, direct holdings of stocks by Households for each age group are obtained by multiplying N_{gt}^{HH}, i.e., the number of households in the US whose head belongs to age group g, by the probability π_{gt}^D of non-zero direct holdings of stocks, and the mean size $\overline{DH_{gt}}$ of direct equity holdings conditional on participation within age group g, respectively. Data on Households' demographics is from the US Census, and data on households' stock holdings is from the Federal Reserve Survey of Consumer Finances (SCF). We later show in Section 3.2 evidence that validates our approach.[16]

Professional Investors

To study the role of financial intermediaries in equity markets over a long historical horizon, we require a measure of professional investors' expectations that (i) spans several decades, (ii) is available at relatively high frequency, and (iii) reflects the beliefs of agents actively operating as intermediaries in financial markets.

[16]To allow for delayed publication of the SCF and the Census results, we lag this data by one year, and hence use $DH_{g(t-1)}$ in Equation 10. This helps reduce look-ahead bias in the later return predictability analysis. That said, lagging or not these quantities has not material effects on our results, because Census data is updated only every 10 years, and data from the SCF is also updated only every three years. We fill the gaps using the most recent information.

A number of existing approaches fail to meet one or more of these requirements. Recent studies infer expectations from capital market assumptions or accounting disclosures by large asset managers and pension funds (e.g., Andonov and Rauh, 2022; Couts et al., 2023; Dahlquist and Ibert, 2024). While informative, these data sources were relatively scarce prior to 2010 and therefore unsuitable for our long-sample analysis. Other surveys focus on highly skilled respondents such as CFOs or economists, including the Graham and Harvey CFO survey, the Livingston survey, and the Survey of Professional Forecasters (SPF). While these are surveys of experts, they do not directly involve individuals that operate as professional financial investors, and the surveys are typically available only at low frequency.[17] Surveys targeting institutional investors more directly, such as Bob Shiller's survey, provide relevant information but are available at monthly frequency only after 2001.

Against these constraints, the Investor Intelligence (II) survey uniquely satisfies our data requirements. The II survey has compiled weekly consensus views of professional investors since 1963 by aggregating recommendations from more than 120 independent financial market newsletters. Since its inception, only four individuals have been responsible for classifying newsletter recommendations as bullish or bearish, ensuring a high degree of methodological consistency over time. To our knowledge the II survey, that recently Greenwood and Shleifer (2014) also interpret as a professional-investor survey, is the longest high-frequency survey of professional stock market participants available for the US market.[18]

While we use II as a measure of expectations in the professional sector of the market, we do not claim this time series tracks directly any specific type of major professional investor. Against the backdrop of a vast set of possible heterogeneous professional investors, what matters for us is that the II survey tracks well the common component of beliefs held by professionals and sophisticated market participants at large. In the next section we show evidence that is consistent with this assertion.

To ease comparability with the retail-expectations index that tracks expectations in percentage points, we follow Greenwood and Shleifer (2014), we obtain the professional expectations index by rescaling the II data to a quantitative measure.[19]

[17] These surveys too have a relatively short time span. The Livingston survey as well as the SPF only began collecting return expectations in the early 1990s, and do so at low frequency (every six months and annually, respectively). The CFO survey data on return expectations is only available since 2000.

[18] Prior research studying the II survey includes Clarke and Statman (1998) and Brown and Cliff (2004).

[19] We follow the approach in Section 1.7 of their paper.

3.2 Expectations Data: Validation

Before conducting the main analysis, we want to investigate the appropriateness of our measures of beliefs held by retail investors and professional investors.

We begin this part of the analysis by focusing on the time-series of retail-investor expectations. In Section 3.1 we took several steps to extend the time-series of retail investor expectations to a long sample period. Our approach is rooted in the following assumptions: (1) by and large, retail investors form extrapolative expectations by extrapolating past returns; (2) taking stock of heterogeneity in belief formation across age groups, while neglecting other characteristics is a simple, yet effective way to capture the consensus expectations of future market returns held by retail investors; (3) within-age group belief-formation parameters are stable, so that a long time-series of retail investors expectations can be constructed using in-sample parameter estimates.

If these assumptions are appropriate, we expect our measure of retail investors' beliefs based on extrapolation to be highly correlated with the raw time-series of beliefs from Gallup. Figure 1, Panel A reports in orange the consensus quantitative expectations collected by Gallup in the sample period 1998-2003. This data is directly used in the construction of EXP^{RI}, also reported in the Panel in green, as explained earlier. The close resemblance of this time-series of raw expectations data with EXP^{RI} indicates that, despite its simplicity, our procedure focusing on the extrapolative component of investor beliefs, and age-based belief heterogeneity in expectations delivers an accurate in-sample representation of the overall beliefs held by retail investors. The 90% correlation between the two series suggests that only minor improvements could be obtained if one were to introduce additional complexity in the measure.

Panel A of Figure 1 also offers insights regarding the out-of-sample performance of our procedure, since it allows us to compare EXP^{RI} with a longer time-series of qualitative expectations (i.e., bullish minus bearish, dashed blue) that Gallup collects for a longer sample period, and is available to us over the period June 1996 to January 2015.[20] Despite the fact that this data is not used at all in constructing our measure, the ability of our retail expectations time-series to match retail investors' expectations data out of sample is striking. Both the full-sample and the out-of-sample correlation between EXP^{RI} and survey-based qualitative expectations is around 70%. Complementing the evidence in Panel A, Panel B of Figure 1 shows that the ability of our metric to capture retail investor beliefs extends beyond the Gallup survey. In particular, we form a first principal component of three series, namely

[20] Greenwood and Shleifer (2014) find that quantitative and qualitative consensus expectations are highly correlated. Qualitative expectations in Figure 1 are constructed using the rescaling procedure outlined in their paper. This rescaling alters the mean and variance of the time-series, but not its time-series variation.

(i) our retail-expectations index that approximates the Gallup survey as shown above, (ii) data on investor expectations of future market conditions from the University of Michigan survey of consumers[21], and (iii) survey data from the American Association of Individual Investors. This principal component is intended to capture the time-series variation in the consensus beliefs of households polled through multiple survey instruments. We then overlay the time-series of this principal component with our measure of retail investor beliefs. We find that the correlation between our index and the principal component is over 80%, indicating that our index of retail investor expectations is successful in capturing broadly held beliefs among retail investors.

Panel C of Figure 1 repeats the comparison of Panel B, but focuses on professional expectations. Specifically we form a principal component of three surveys of expert beliefs, namely, the Investor Intelligence Survey, the Livingston Survey, and Robert Shiller's survey of investment managers. We then compare it with the II survey which we use as a measure of professional investors' beliefs in our main analysis. Here too, we find a strong comovement between the two series, suggesting our attempt at summarizing beliefs held by professional market participants is reasonable.

To build further confidence in our procedure and our empirical choices, we also follow earlier work (e.g., Gennaioli and Shleifer, 2018) arguing that to the extent that surveys reflect actual investor beliefs, they should align with portfolio choice. Therefore, we investigate empirically the relation between beliefs and capital allocation to equities. To track retail investors, we concentrate on flows into equity mutual funds, measured using data from the Investment Company institute. For professional investors, we follow recent work arguing that tracking investment vehicles such as separate accounts captures well institutional investors' demand (e.g., Huang et al., 2025). Using data from Morningstar, we construct quarterly percentage equity flows into both fund types, and relate them to contemporaneous changes in investor beliefs.[22]

The results, in Table 2, provide support to our survey-based approach to measuring institutional and retail investor beliefs. In Panel A, we find evidence of statistically positive and significant relation between equity mutual fund flows and retail investors' beliefs, while the

[21] The question from the University of Michigan survey of consumers is *"What do you think is the percent chance that a one thousand dollar investment in a diversified stock mutual fund will increase in value in the year ahead, so that it is worth more than one thousand dollars one year from now?"*. For consistency with other data sources, we construct a balance statistic (i.e., % bullish minus % bearish).

[22] We focus on changes in beliefs because flows are inherently marginal, i.e., they capture changes in asset demand that are more naturally linked to revisions in expectations than to expectation levels (e.g., Berk and Green, 2004). This choice is also econometrically preferable, since as noted in prior work fund flows are persistent and display a marked downward trend. Given these properties, regressions in levels can overstate the relation between outcome and explanatory variables in finite sample. Using changes in the explanatory variable reduced this concern (Granger and Newbold, 1974).

regression does not detect any significant link between professional expectations and equity fund flows. This result is obtained in univariate and bivariate regressions where we explicitly control for the beliefs of professional investors. The result survives the inclusion of controls. In Panel B, we find a symmetric result for professional flows, which hold a statistically significant relation with professional investor beliefs, but not with the expectations held by retail investors. Overall, this result gives us confidence in our baseline approach.

Finally, we note that expectations from surveys likely reflect true expectations with noise. Thus in Appendix F, we investigate how the estimation approach presented in the previous section fairs in the presence of measurement error in the expectations data. We consider measurement errors in both professional and retail expectations, calibrated to the data, as well as correlated measurement errors, as discussed more in detail later in Section 6, as well as in Appendix F. In short, the results which we describe more in detail in the aforementioned sections, indicate that under the null of no-professional influence on asset prices, we would not be able to reject the null of no-intermediary influence on asset prices, and we would recover a process of latent influence w_t that is considerably different from the one obtained in our empirical analysis.

3.3 Households' Stock Ownership: Administrative Data

While the Kalman filter is our primary method for measuring the influence of households and professionals in the equity market, we also benchmark our results against administrative data. Following Stambaugh (2014b), we use the Financial Accounts of the United States (formerly the Flow of Funds, FoF), published by the Federal Reserve Board, to track retail investors' stock market ownership. A key limitation of the FoF is that the Household sector is a residual category that includes entities such as non-profit organizations. To address this issue, we rely on French (2008), who provides accurate estimates of households' direct stock ownership for 1980–2007. For 1963–1979 and 2008–2023, we combine supplemental FoF tables with data on individuals' mutual fund ownership from the Investment Company Institute, data on the non-profit sector size from the National Association of Non-Profit Organizations and their Executives (NANOE), retail ownership of closed-end funds (Wang and Nanda, 2011), and retail ownership of ETFs from Deutsche Bank reports. Appendix Section B details the construction of the resulting time series. We later compare this series to the one recovered using the Kalman filter.

3.4 Prices and Returns

We obtain the price-dividend ratio from Amit Goyal's website. We use this time-series as part of the measurement equation in the Kalman filter estimation. To test for time-series aggregate return predictability, we form a monthly time series of cumulative yearly excess return on a value weighted portfolio of US stocks. We source returns data from Ken French's website, and the 1-year risk-free rate from the Federal Reserve website.

4 Retail Investor Influence

4.1 Kalman Filter Estimates: Four New Facts

Our empirical approach combines survey-based expectations of retail and institutional investors with a structural model of latent market impact to estimate the time-varying influence of households on asset prices. Figure 2 plots these estimates in gray; confidence intervals are bootstrapped. Table 5 reports the Kalman filter parameter estimates and their bootstrapped distributions. Finally, Figure 3 presents hypothesis tests that compare the estimates from the data with their bootstrapped counterparts under the joint null of $w_0 = 1$, $\gamma = 0$, $\phi = 0$, i.e., retail investor influence fluctuates around 1. While this null is in line with the notion of "no intermediary influence", i.e., $w_t = 1$, our empirical estimates could still recover some fluctuation due to the non-zero variance of trend and cycle shocks, ξ_t and η_t (see Section 2.2). At the same time, these shocks are assumed to be mean-zero, so that the recovered dynamics of w_t will on average align to the null of no intermediary influence.[23]

Figure 2 reveals four main facts about household influence on stock prices over time. First, at the beginning of the sample, households exert most of the influence on market valuation. This implies little role for intermediaries or professional investors in the early 1960s. This interpretation is generally consistent with both administrative data on household portfolios and prior work showing that the stock market was then largely non-intermediated, with households holding stocks mostly directly. Consistent with this evidence, Panel A of Figure 3 shows that we cannot reject the null of full household influence at the start of the sample (i.e., $w_0 = 1$).

Second, the estimated time series of investor influence in Figure 2 slopes sharply downward. A simple way to quantify this decline, and test its significance, is through the trend

[23]For bootstrapped confidence intervals and parameter distributions, we sample disturbances with replacement from a model parameterized by the estimates obtained from the data. For hypothesis testing, bootstrapping instead generates time series for the relevant processes under the aforementioned null hypothesis.

parameter γ. Table 5 shows that γ is negative in 90% of the bootstrapped samples. Panel B of Figure 3 further shows that if γ were zero in the data, that is, if households' influence did not decline over time, the probability of estimating a value as negative as the one recovered by the Kalman filter from the data would be only 0.8%. The decline is therefore not only statistically significant but also economically large: over the sample, household influence falls by close to 1% per year. Overall, as Figure 2 shows, retail investors' influence declines from about 1 to about 0.5 over the last 60 years, a roughly 50% drop.[24]

Third, Figure 2 shows that the estimated series for retail investor influence differs substantially from the value of w_t implied by the null of no intermediary influence, represented by the dashed horizontal line at 1. In the early part of the sample, the confidence intervals for estimated w_t still include this null value, but for a large share of the sample they do not. Using the 95% confidence intervals in Figure 2, this occurs for about 80% of the sample, or roughly 50 years. Panel D of Figure 3 formalizes this result by comparing the average retail influence recovered from the data, 0.731, with the average influence recovered under the null hypothesis of no intermediary influence (i.e., bootstrapping under $w_0 = 1$, $\phi = 0$, and $\gamma = 0$). The figure shows that under the null of no-intermediary influence, the probability of recovering an average retail influence as low as the one observed in the data throughout the sample is essentially zero.

Fourth, Figure 2 compares our estimated series for household influence with the series for households' direct stock ownership, shown in blue. This ownership series can be interpreted as the influence households would have if they affected prices only through direct equity holdings. Previous work arguing that households' role in asset pricing has declined has often relied on this direct-ownership series as a way to quantify such a decline (e.g., Stambaugh, 2014b). However, direct ownership is not the only channel through which households can matter for prices. First, even when owning shares indirectly, household demand shifts can affect prices through fund flows. Second, as households increasingly invest through passive vehicles such as ETFs and passive mutual funds, or when managers face strong incentives to track benchmarks (e.g., Basak and Pavlova, 2013), intermediary beliefs may matter less for prices than measures of households' delegation of financial decisions to professionals would suggest. Third, delegation contracts and their enforcement may make intermediaries act as a veil through which household expectations and risk appetite continue to shape prices.

For these reasons, households' direct ownership need not measure their true influence on asset prices. Until now, the extent to which households matter beyond their direct holdings has remained unknown. Figure 2 provides new evidence on this margin. Although both

[24] A back-of-the-envelope calculation implies an approximate decline of $\hat{\gamma} \times T = -0.0007 \times 732$ months $= -0.5124$.

direct participation and estimated influence decline over the sample, household influence remains consistently above the level implied by direct ownership alone. In other words, as households shift from direct to indirect ownership over time, intermediation does not fully eliminate their influence on prices, possibly because contractual and fiduciary obligations tie professional investors' behavior to household preferences and beliefs.

Taken together, these results uncover new time-series properties of households' influence on asset prices. The null of no intermediary influence overstates household influence, and increasingly so over time. At the same time, the results suggest that the extent of household intermediation is a poor proxy for the influence of intermediaries in the market. We next turn to the determinants of this newly uncovered time-series variation in household influence.

5 The Determinants of Retail Investors' Influence

In this section, we offer an in-depth analysis into the determinants of retail investors' influence. The analysis mimics the structure of our econometric framework, in that we analyze separately the drivers of the cyclical (i.e., transitory) and the stochastic-trend (i.e., permanent) components of households' influence. Figure 4 presents these two components graphically. Panel A displays the transitory component $\hat{u}_t$. Panel B plots the stochastic trend, i.e., the time-series of τ, after removing its deterministic component, $\tilde{\tau} \equiv \hat{\tau}_t - \hat{\gamma}t$. In what follows, we will formally analyze the driving forces between both sources of variation through standard regression-based techniques.

5.1 Cyclical Variation in Retail Investors' Influence

We begin by examining the transitory component of retail investor influence. We group the explanatory variables into three broad categories, each chosen for its potential to account for temporary movements in household influence. The first includes measures of aggregate risk and household risk tolerance, which may affect households' willingness to bear risk and, in turn, their cyclical influence on prices. The second captures household financial and labor-market conditions, which may shape households' ability to participate in equity markets and absorb risky assets over the cycle. The third proxies for investor attention, motivated by the idea that salient market conditions may temporarily increase households' engagement with financial markets. This classification helps distinguish between channels operating through households' willingness to take risk, their capacity to do so, and their attention to the market.

Table 6 reports the regression results, while Figure 5 plots smoothed time series for a subset of the explanatory variables alongside $\hat{u}_t$.

Our first conjecture is that temporary fluctuations in household influence reflect transitory changes in households' willingness to bear risk. If so, measures of household risk tolerance and aggregate risk conditions should help explain movements in $\hat{u}_t$. The evidence in Panel A of Table 6 is broadly consistent with this view. The clearest result concerns the Surplus Consumption Ratio (SCR) of Campbell and Cochrane (1999), which measures current consumption relative to households' habit level. Because higher SCR is associated with lower risk aversion, the positive coefficient on SCR suggests that households exert greater temporary influence on prices when their risk tolerance is higher. Quantitatively, a one-standard-deviation increase in SCR raises the cyclical component of household influence by about 0.247 standard deviations ($t = 3.52$). This result is consistent with the idea that greater household risk tolerance increases stock-market participation and, with it, households' effect on prices (Santos and Veronesi, 2022).

The same logic implies that household influence should weaken when aggregate risk rises. Consistent with this prediction, the recession indicator REC enters negatively, implying that retail investor influence is on average 0.55 standard deviations lower in NBER recession months than in expansions. We find a similar, though somewhat weaker, pattern for 12-month trailing stock-return volatility (VOL): higher volatility is associated with lower retail influence (-0.134, $t = -1.70$). Taken together, these results suggest that short-run fluctuations in retail influence are closely related to variation in household risk tolerance and broader market risk conditions.

Panel A also considers whether cyclical variation in household influence is related to the balance-sheet capacity of key financial intermediaries. To assess this channel, we include two proxies for the financial constraints of banks and broker-dealers, the Intermediary Capital Ratio (ICR, He et al., 2017) and broker-dealer leverage (LEV, Adrian et al., 2014). We do not find evidence that either variable significantly explains cyclical movements in retail investor influence.[25]

We next consider the hypothesis that cyclical variation in household influence reflects fluctuations in households' capacity to participate in equity markets. Panel B examines this possibility using household-finance and labor-market variables. The strongest evidence within this group concerns labor-market conditions, proxied by the employment-to-population ratio (EPR). If employment helps households overcome participation costs such as brokerage fees and transaction costs (e.g., Favilukis, 2013), stronger labor-market conditions should be associated with greater household influence. The data support this prediction: EPR is pos-

[25] This null result does not imply that intermediary capital ratios are unimportant for asset prices more generally. Existing evidence often comes from markets in which broker-dealers and banks play a particularly central intermediation role (e.g., CDS markets), whereas equity-market intermediation involves many non-bank institutions.

itively associated with $\hat{u}_t$, and the coefficient is significant at the 5% level (0.093, $t = 2.58$). Thus, stronger labor-market conditions appear to coincide with greater household influence on prices.

A related possibility is that household leverage moves with households' willingness or ability to take financial risk. In this spirit, we consider the aggregate household debt-to-income ratio (DTI). The positive coefficient on DTI is qualitatively consistent with the mechanism in Santos and Veronesi (2022), in which higher household risk tolerance is associated with higher debt-to-income ratios and greater risky-asset holdings. In the data, we likewise find a positive relation between DTI and household influence, although the estimate is only marginally significant at the 10% level.

The remaining household-finance variables in Panel B provide little additional evidence for this channel. In particular, the fraction of households reporting worse financial conditions than a year earlier (PFDET), personal dividend income (PDI), and the equity-to-financial-assets ratio (ETA) do not significantly explain cyclical variation in retail influence.

Finally, we consider the hypothesis that temporary fluctuations in household influence reflect changes in investor attention. Panel C evaluates this idea using indicator variables designed to capture salient market conditions, such as extreme market returns, as well as an indicator for positive market returns. The former are motivated by the idea that extreme return realizations are especially attention-grabbing and may induce greater household participation (e.g., Barber and Odean, 2007), while the latter is motivated by evidence that investors monitor markets more closely in periods of positive returns than in periods of negative returns (e.g., Karlsson et al., 2009). We find little evidence that these attention proxies explain cyclical movements in household influence.

Panels D to F of Table 6 repeat the analysis at the 12-month horizon, using the annual rolling average of $\hat{u}_t$ as the dependent variable and annual differences for non-stationary explanatory variables. The results are broadly similar to those at the monthly horizon. Overall, the evidence points to channels operating through households' willingness and capacity to participate in equity markets.

5.2 Permanent Variation in Retail Investors' Influence

In this subsection we complement the analysis of the cyclical component of retail investors' influence with an investigation of what determines the long-lasting (i.e., permanent) changes in such an influence. Our goal is to link long-lasting changes in retail investors' influence, that are captured in our model by the stochastic trend process τ, with historical events that have the potential for long-lived effects on retail investors' influence in the market.

To identify candidate events, we adopt a procedure that is aided by the use of large-language model. Specifically, we proceed in three steps: (i) we identify a list of candidate events; (ii) we classify the likely economic impact of each candidate event on retail investors' influence in the stock market; (iii) we investigate whether events that are likely to lead to increased or reduced retail investors' influence, are indeed linked to a corresponding predictable variation in the permanent component of our extracted retail investors' weights.

5.2.1 Identifying Candidate Events

We begin by constructing a list of candidate events via a web search. We search primarily for three types of significant events that can alter the influence of either retail investors or institutional investors in the market: (i) regulatory and legal events; (ii) market events and financial innovation; (iii) social finance. This manual search contains 39 events. We then rely on an LLM to source additional events, leading to a total of 83 candidate events.[26] More than half of these events are regulatory in nature, with the remainder roughly equally split between the other two aforementioned categories. The complete list of candidate events is reported in the Appendix Table C.1.

5.2.2 Classifying Events

Having formed a dataset of candidate events, each featuring a brief description, we then classify these events into two groups, namely those that are predicted to facilitate retail investors' influence, and those that are predicted to curtail it. The classification is done in two ways. The first approach is manual, as we analyze the nature of each event via web searches and we classify it accordingly on the basis of our subjective judgment. The second approach to the classification involves a large-language model. Specifically, for each candidate event we prepare a self-contained textual description about the event. To ensure that the each description is sufficient to understand the nature of the event, yet it avoids any of the researcher's own judgment to anchor the subsequent LLM interpretation, we rely on suggestions from OpenAI ChatGPT 5.2 thinking model.

We then use the OpenAI API to access the processing capabilities of OpenAI o4-mini reasoning model. We ask the model to analyze and classify, one by one and independently of each other each event based on the provided description. The prompts used to complete this step are in Appendix Section C.1. The result of this classification is in Table C.1.

[26] In this step, we use OpenAI ChatGPT, model 5.2.

5.2.3 Results

We use the classifications outlined above to perform predictive regressions. The idea of these regressions is simple, as we conjecture that positive shocks should lead to a long-lived increase in retail investors' influence, while negative shocks should be associated with a long-lived decline in retail investors' influence. Since long-lived shocks are well captured in our econometric model by the stochastic trend component in the model $\tilde{\tau}$, our goal is to assess whether positive and negative shocks are indeed linked to an increase in $\tilde{\tau}$ in the future.

In this analysis we need to resolve a tension. on the one hand running short-horizon predictive regressions has the advantage of more convincingly linking events to the future behavior of retail investors' influence. On the other hand, when a historical event such as a regulatory reform takes place, the effect of this reform on retail investors' influence can take some time to materialize. To address this trade-off, we estimate Jordà (2005) with horizons ranging from 0 months (i.e., contemporaneous effects) to 60 months. We show the estimates from this analysis in Figure 6, where Panel A concerns the manual classification of events, while Panel B refers to the LLM-based one.

The results show that, consistent with our intuition, events flagged as positive shocks to households' influence, lead to a long-lived increase of retail investors' influence. Conversely, events flagged as negative shocks to households' influence, lead to a long-lived decline in retail investors' influence, although the latter effects is a bit smaller and it appears to be more delayed. In Table 7 we complement this graphical evidence with a formal test of whether the documented impact of positive and negative shocks on future retail investors' influence is statistically significant. Regression analysis also allows to formally test whether the difference in the impact of positive and negative shocks for future retail investors' influence is statistically significant. We find this to be the case. For both the manual (Panel A) and the LLM-based classification (Panel B), we show that the differences Δ in the documented effects are positive and statistically significant at the 1% level.

Finally, in Figure 7 we perform a placebo analysis, in which we generate 1000 sets of fictitious events. Each set has the same number of positive and negative shocks as in our combined classification, but the event dates and the directional impact are randomized in each of the aforementioned sets. Using these fictitious dates, we repeat the analysis of Figure 6. The figure reveals that, when events are generated and classified at random, they have no predictive power for future retail investors' influence. This result contrasts sharply with the one obtained when we use the collection of events and the classification outlined above, building confidence that the results presented in this section offers a meaningful insight.

6 Robustness

We assess the robustness of our results along three dimensions. First, we ask whether the estimated time series of household influence is sensitive to alternative model specifications. Second, we study whether the Kalman filter has a mechanical tendency to generate a declining role for retail investors even when the true data-generating process features no role for institutions. Third, we examine whether measurement error in the expectations series could spuriously push the model estimation toward rejecting the null hypothesis of no-intermediary influence. Across all three exercises, the central message of the paper remains intact.

Our first set of checks varies both the measurement equation and the estimation procedure. In the baseline specification, market valuations are linked to retail and professional expectations through the unadjusted monthly log dividend-price ratio. We then consider several alternative specifications. One replaces the raw dividend-price ratio with a version corrected for structural breaks in valuation, following Lettau and Van Nieuwerburgh (2008). A second removes from the dividend-price ratio the variation associated with household risk aversion, intermediary risk-bearing capacity, and macroeconomic uncertainty, by orthogonalizing it with respect to the Surplus Consumption Ratio, the Intermediary Capital Ratio, and the financial uncertainty measure of Jurado et al. (2015). A third changes the law of motion for the latent weights by shutting down the deterministic drift term, i.e., setting $\gamma = 0$ rather than estimating it. Finally, we assess numerical sensitivity by repeating the baseline estimation with a substantially finer optimization grid.

These alternative specifications deliver weight estimates that are highly similar to the baseline series. Figure 8 shows that all estimated series exhibit the same broad evolution over time: household influence is high early in the sample and declines materially thereafter. Table D.1 further shows that the associated parameter estimates are stable across specifications. As an additional benchmark, we form a simple ensemble estimate by averaging the filtered weights across models within each month. The ensemble closely tracks the baseline series, suggesting that the main result is not driven by any single modeling choice. Figure D.1 reaches the same conclusion from a different angle. The correlations across the alternative weight series are high in levels and remain sizable after detrending, indicating that the common variation is not merely due to a shared secular trend. Taken together, these exercises show that our estimates of household influence are robust to plausible changes in the measurement equation, the state dynamics, and the optimization routine.

The second exercise asks whether the filtering procedure itself is predisposed to recover a declining role for households, even if institutions are in fact irrelevant for prices. To address this concern, we simulate data under the null of institutional irrelevance, setting

$w_t = 1$ throughout the sample and assuming that the dividend-price ratio loads only on retail expectations plus measurement noise. We then re-estimate the full model repeatedly on these simulated data. The results, reported in Figure 9 and Table E.1, show that the filter is able to recover a constant weight process centered around the true value of one. Moreover, the associated parameter estimates move in the correct direction: both the intercept and the time-series filtered weights are close to 1, and the filter assigns little role to cyclical components or trend dynamics when these are absent by construction. This exercise is important because it shows that the downward-sloping pattern recovered in the data is not an artifact of the estimation procedure itself. If the true process features no intermediary influence, the filter does not mechanically generate a negative trend.

Our final exercise examines the role of noisy expectation measures. In the main analysis, both retail and professional beliefs are observed through survey-based proxies, and it is natural to worry that error in these inputs may distort the recovered weights. We therefore simulate a setting in which the true dividend-price ratio depends on latent investor expectations, while the econometrician only observes noisy counterparts. The noise process is calibrated from the data using the discrepancy between survey expectations and the corresponding principal-component series, including the covariance between retail and professional measurement errors. We then re-estimate the model under the scenario of correlated noise in expectations.

The results — presented in Figure 10, and Table F.1 — are informative. When expectations are mismeasured, the filter has difficulty recovering the correct level of the latent weights: the estimated intercept is biased downward and the recovered series is less tightly centered around the true value. Importantly, however, the simulation does not produce the main empirical pattern from the data, namely a pronounced negative trend in household influence. In other words, although measurement error in expectations can affect the average level around which the filtered weights fluctuate, it does not generate the secular decline that is central to our findings. This suggests that belief mismeasurement is unlikely to be the source of the baseline results.

Overall, the robustness exercises support two conclusions. First, the estimated decline in household influence is stable across a range of alternative specifications and estimation choices. Second, the Kalman filter does not mechanically recover a downward trend, nor does plausible mismeasurement in expectations data generate one when the true latent process is flat. The evidence therefore supports the interpretation that the time-series variation uncovered in the main analysis reflects a genuine feature of the data rather than a modeling artifact.

7 Conclusion

This paper studies whether the rise of financial intermediation has changed whose beliefs matter for aggregate stock-market valuation. Rather than testing intermediary asset-pricing theories through indirectly measured risk preferences or cross-market comparisons, we take a within-market, belief-based approach in the US stock market, leveraging the availability of survey expectations for retail investors and professionals, and the substantial variation in delegation over the last six decades.

Our central contribution is a structural present-value framework in which the market price-dividend ratio reflects a weighted combination of retail and professional return expectations, alongside traditional discount-rate drivers. We treat the relative influence weight as a latent time series with both a trend and a cyclical component, and we recover it using Kalman-filtering techniques. This approach allows the data to discipline how influence evolves over time, rather than equating influence mechanically with administrative measures of direct versus indirect ownership.

The estimates deliver three main takeaways. First, the influence of household beliefs on market valuation declines meaningfully over time. In the early part of the sample, the weight on retail expectations is close to one, consistent with a market in which households are the dominant force in price formation. By the end of the sample, retail influence falls to roughly one-half, implying a substantial, yet incomplete, shift toward professional investors' beliefs playing a larger role in equilibrium prices. Importantly, we can reject the frictionless null of no intermediary influence for most of the sample, indicating that intermediation is not merely a passive "veil" over household-driven pricing.

Second, rising delegation does not imply that households become irrelevant. While our recovered influence series comoves with standard administrative indicators of intermediation, it differs sharply in magnitude: households retain considerably more influence than implied by direct-ownership statistics. A natural interpretation is that even when households hold equities indirectly, they remain principals who shape intermediaries' decisions through contracting, monitoring, and the ability to reallocate capital across vehicles and managers. In this sense, the delegation process appears to tilt price determination toward professionals without fully displacing the household sector, pointing to a more nuanced equilibrium than the stark "intermediaries dominate" view.

Beyond documenting secular changes, the paper also sheds light on why influence shifts. The cyclical component of retail influence is related to states of risk and macroeconomic conditions in intuitive ways: retail influence tends to rise when households appear more risk tolerant and to fall in recessions or following elevated market volatility. The permanent

component exhibits longer-lived movements that we connect to major regulatory, social, and market-structure changes. By assembling and classifying a large set of historically salient events—supported by a large-language-model workflow—we show that shocks predicted to favor households (professionals) are followed by persistent increases (declines) in the long-run component of retail influence, helping reconcile the latent influence series with the evolving institutional environment of US equity markets.

These results have several implications. For asset-pricing tests, they highlight the value of belief-based identification: when beliefs are observable, one can test intermediary theories while explicitly controlling for households, mitigating joint-hypothesis concerns tied to unobserved preferences. For the macrostructure literature, they suggest that market organization affects equilibrium pricing not only through constraints and balance-sheet capacity, but also through whose expectations receive greater weight in valuation. For behavioral finance, they indicate that the mapping from beliefs to prices is not stable over time: the predictive content of expectations depends on which investor group is marginal, and delegation can shift that margin in economically meaningful ways.

Overall, the evidence supports a view in which intermediation matters for stock-market valuation, but not in a way that eliminates the household sector. Delegation raises the role of professional beliefs in equilibrium pricing, while households retain substantial influence through the economic frictions and institutional arrangements that govern delegated investment. By measuring this influence directly from beliefs—and showing that it is both economically meaningful and asset-pricing relevant—the paper provides a unified framework linking intermediary asset pricing, behavioral expectations, and the evolution of market macrostructure.

References

Adrian, T., Etula, E., and Muir, T. (2014). Financial intermediaries and the cross-section of asset returns. *The Journal of Finance*, *69*(6), 2557–2596.

Ahmadi, M., Khashei, M., and Zeinal Hamadani, A. (2025). Wind power forecasting: A hybrid multi-layer perceptron framework with adaptive noise reduction and error correction. *Computers and Electrical Engineering*, *128*, 110689. https://doi.org/https://doi.org/10.1016/j.compeleceng.2025.110689

Aiolfi, M., and Timmermann, A. (2006). Persistence in forecasting performance and conditional combination strategies. *Journal of Econometrics*, *135*(1-2), 31–53.

Andonov, A., and Rauh, J. D. (2022). The return expectations of public pension funds. *The Review of Financial Studies*, *35*(8), 3777–3822.

Arnsberger, P., Ludlum, M., Riley, M., Stanton, M., et al. (2008). A history of the tax-exempt sector: An soi perspective. *Statistics of Income Bulletin*, *27*(3), 105–135.

Baker, M., and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129–152. https://doi.org/10.1257/jep.21.2.129

Baker, M. P., Wurgler, J., and Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, *104*(2), 272–287. https://doi.org/10.1016/j.jfineco.2011.11.002

Baker and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Barber, B. M., and Odean, T. (2007). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, *21*(2), 785–818.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2015a). X-capm: An extrapolative capital asset pricing model. *Journal of Financial Economics*, *115*(1), 1–24.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2015b). X-capm: An extrapolative capital asset pricing model. *Journal of Financial Economics*, *115*(1), 1–24. https://doi.org/10.1016/j.jfineco.2014.08.007

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics*, *129*(2), 203–227. https://doi.org/10.1016/j.jfineco.2018.04.007

Baron, M., and Muir, T. (2022). Intermediaries and asset prices: International evidence since 1870. *The Review of Financial Studies*, *35*(5), 2144–2189.

Basak, S., and Pavlova, A. (2013). Asset prices and institutional investors. *American Economic Review*, *103*(5), 1728–1758.

Berk, J. B., and Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, *112*(6), 1269–1295. https://doi.org/10.1086/424739

Bordalo, P., Gennaioli, N., La Porta, R., and Shleifer, A. (2019). Diagnostic expectations and stock returns. *The Journal of Finance*, *74*(6), 2839–2874. https://doi.org/10.1111/jofi.12833

Bordalo, P., Gennaioli, N., La Porta, R., and Shleifer, A. (2024a). Belief overreaction and stock market puzzles. *Journal of Political Economy*, *132*(5), 1450–1484.

Bordalo, P., Gennaioli, N., La Porta, R., and Shleifer, A. (2024b). *Finance without exotic risk* (tech. rep.). National Bureau of Economic Research.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2018). Diagnostic expectations and credit cycles. *The Journal of Finance*, *73*(1), 199–227. https://doi.org/10.1111/jofi.12586

Brown, G. W., and Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, *11*(1), 1–27.

Campbell, J. Y., and Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, *107*(2), 205–251.

Campbell, J. Y., and Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, *1*(3), 195–228. https://doi.org/10.1093/rfs/1.3.195

Canova, F. (1998). Detrending and business cycle facts. *Journal of Monetary Economics*, *41*(3), 475–512. https://doi.org/10.1016/S0304-3932(98)00006-3

Cassella, S., and Gulen, H. (2018). Extrapolation bias and the predictability of stock returns by price-scaled variables. *Review of Financial Studies*, *21*(2), 785–818.

Clark, P. K. (1987). The cyclical component of u.s. economic activity. *The Quarterly Journal of Economics*, *102*(4), 797–814. https://doi.org/10.2307/1884282

Clarke, R. G., and Statman, M. (1998). Bullish or bearish? *Financial Analysts Journal*, *54*(3), 63–72.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of Finance*, *66*(4), 1047–1108.

Cochrane, J. H. (2017). Macro-finance. *Review of Finance*, *21*(3), 945–985.

Coskun, H., Achilles, F., DiPietro, R., Navab, N., and Tombari, F. (2017). Long short-term memory kalman filters: Recurrent neural estimators for pose regularization. *Proceedings of the IEEE international conference on computer vision*, 5524–5532.

Couts, S. J., Gonçalves, A. S., and Loudis, J. (2023). The subjective risk and return expectations of institutional investors. *Fisher College of Business Working Paper*, *14*.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461–1499.

Da, Z., Engelberg, J., and Gao, P. (2015). The sum of all fears: Investor sentiment and asset prices. *Review of Financial Studies*, *28*(1), 1–32. https://doi.org/10.1093/rfs/hhu072

Da, Z., Huang, X., and Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, *140*(1), 175–196.

Dahlquist, M., and Ibert, M. (2024). Equity return expectations and portfolios: Evidence from large asset managers. *The Review of Financial Studies*, *37*(6), 1887–1928.

Duffie, D. (2022). *Fragmenting markets: Post-crisis bank regulations and financial market liquidity*. Walter de Gruyter GmbH & Co KG.

Favilukis, J. (2013). Inequality, stock market participation, and the equity premium. *Journal of Financial Economics*, *107*(3), 740–759.

French, K. R. (2008). Presidential address: The cost of active investing. *Journal of Finance*, *63*(4), 1537–1573.

Gennaioli, N., and Shleifer, A. (2018). A crisis of beliefs: Investor psychology and financial fragility.

Giglio, S., Maggiori, M., Stroebel, J., and Utkus, S. (2021). Five facts about beliefs and portfolios. *American Economic Review*, *111*(5), 1481–1522.

Goyal, A., and Welch, I. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, *21*(4), 1455–1508.

Granger, C. W. J., and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111–120.

Greenwood, R., and Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, *27*(3), 714–746.

Haddad, V., and Muir, T. (2021). Do intermediaries matter for aggregate asset prices? *The Journal of Finance*, *76*(6), 2719–2761.

Haddad, V., and Muir, T. (2025). Market macrostructure: Institutions and asset prices. *Annual Review of Financial Economics*, *17*.

Hall, P., Horowitz, J. L., and Jing, B.-Y. (1995). On blocking rules for the bootstrap with dependent data. *Biometrika*, *82*(3), 561–574.

Harvey, A. C. (1990). Forecasting, structural time series models and the kalman filter.

Harvey, A. C., and Jaeger, A. (1993). Detrending, stylized facts and the business cycle. *Journal of Applied Econometrics*, *8*(3), 231–247. https://doi.org/10.1002/jae.3950080302

He, Z., Kelly, B., and Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, *126*(1), 1–35.

He, Z., and Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*, *103*(2), 732–770.

He, Z., and Krishnamurthy, A. (2018). Intermediary asset pricing and the financial crisis. *Annual Review of Financial Economics*, *10*(1), 173–197.

Higgins, E. T. (1996). Activation: Accessibility, and salience. *Social psychology: Handbook of basic principles*, 133–168.

Huang, S., Lu, X., Song, Y., and Xiang, H. (2025). Remeasuring scale in active management.

Jin, L. J., and Sui, P. (2022). Asset pricing with return extrapolation. *Journal of Financial Economics*, *145*(2), 273–295.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*(3), 1177–1216.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review*, *93*(5), 1449–1475.

Kahneman, D., and Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the national academy of sciences*, *107*(38), 16489–16493.

Kahneman, D., Frederick, S., et al. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and biases: The psychology of intuitive judgment*, *49*(49-81), 74.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems.

Karlsson, N., Loewenstein, G., and Seppi, D. (2009). The ostrich effect: Selective attention to information. *Journal of Risk and Uncertainty*, *38*(2), 95–115.

Kuttner, K. N. (1994). Estimating potential output as a latent variable. *Journal of Business & Economic Statistics*, *12*(3), 361–368. https://doi.org/10.1080/07350015.1994.10524551

La Porta, R. (1996). Expectations and the cross-section of stock returns. *The Journal of Finance*, *51*(5), 1715–1742. https://doi.org/10.1111/j.1540-6261.1996.tb05223.x

Lee, C. M. C., Shleifer, A., and Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance*, *46*(1), 75–109. https://doi.org/10.1111/j.1540-6261.1991.tb03746.x

Lettau, M., and Van Nieuwerburgh, S. (2008). Reconciling the return predictability evidence: The review of financial studies: Reconciling the return predictability evidence. *The Review of Financial Studies*, *21*(4), 1607–1652.

Ma, Y., Xiao, K., and Zeng, Y. (2022). Mutual fund liquidity transformation and reverse flight to liquidity. *The Review of Financial Studies*, *35*(10), 4674–4711.

Malmendier, U., and Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, *126*(1), 373–416.

Matisko, P., and Havlena, V. (2013). Noise covariance estimation for kalman filter tuning using bayesian approach and monte carlo. *International Journal of Adaptive Control and Signal Processing*, *27*(11), 957–973.

McCarthy, O., and Hillenbrand, S. (2025). Heterogeneous beliefs and stock market fluctuations. *Available at SSRN 3944887*.

Morley, J. C., Nelson, C. R., and Zivot, E. (2003). Why are the beveridge–nelson and unobserved-components decompositions of gdp so different? *The Review of Economics and Statistics*, *85*(2), 235–243. https://doi.org/10.1162/003465303765299765

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica*, *29*(3), 315–335. https://doi.org/10.2307/1909635

Nagel, S., and Xu, Z. (2022). Asset pricing with fading memory. *The Review of Financial Studies*, *35*(5), 2190–2245.

Neal, R., and Wheatley, S. M. (1998). Do measures of investor sentiment predict returns? *Journal of Financial and Quantitative Analysis*, *33*(4), 523–547.

Nelson, C. R. (1988). Spurious trend and cycle in the state space decomposition of a time series with a unit root. *Journal of Economic Dynamics and Control*, *12*(2-3), 475–488. https://doi.org/10.1016/0165-1889(88)90051-6

Newey, W. K., and West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies*, *61*(4), 631–653.

Politis, D. N., and Romano, J. P. (1994). The stationary bootstrap. *Journal of the American Statistical association*, *89*(428), 1303–1313.

Qiu, L. X., and Welch, I. (2006). Investor sentiment measures. *NBER Working Paper*, (w10794).

Rogerson, W. P. (1985). Repeated moral hazard. *Econometrica: Journal of the Econometric Society*, *53*(1), 69–76.

Santos, T., and Veronesi, P. (2022). Leverage. *Journal of Financial Economics*, *145*(2), 362–386. https://doi.org/10.1016/j.jfineco.2021.09.001

Scharfstein, D. (2018). Presidential address: Pension policy and the financial system. *Working Paper*.

Schneider, R., and Georgakis, C. (2013). How to not make the extended kalman filter fail. *Industrial & Engineering Chemistry Research*, *52*(9), 3354–3362.

Spear, S. E., and Srivastava, S. (1987). On repeated moral hazard with discounting. *The Review of Economic Studies*, *54*(4), 599–617.

Stambaugh, R. F. (2014a). Presidential address: Investment noise and trends. *Journal of Finance*, *69*(4), 1415–1453.

Stambaugh, R. F. (2014b). Presidential address: Investment noise and trends. *The Journal of Finance*, *69*(4), 1415–1453.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288–302. https://doi.org/10.1016/j.jfineco.2011.05.011

Timmermann, A. (2006). Forecast combinations. *Handbook of economic forecasting*, *1*, 135–196.

Van Binsbergen, J. H., and Koijen, R. S. (2010). Predictive regressions: A present-value approach. *The Journal of Finance*, *65*(4), 1439–1471.

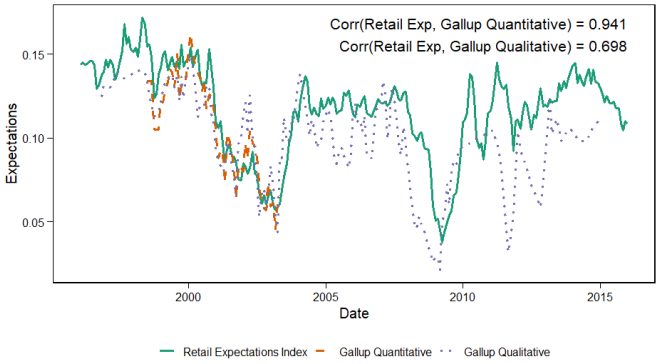
Vissing-Jorgensen, A. (2003). Perspectives on behavioral finance: Does" irrationality" disappear with wealth? evidence from expectations and actions. *NBER macroeconomics annual*, *18*, 139–194.

Wang, Z. J., and Nanda, V. (2011). Payout policies and closed-end fund discounts: Signaling, agency costs, and the role of institutional investors. *Journal of Financial Intermediation*, *20*(4), 589–619.

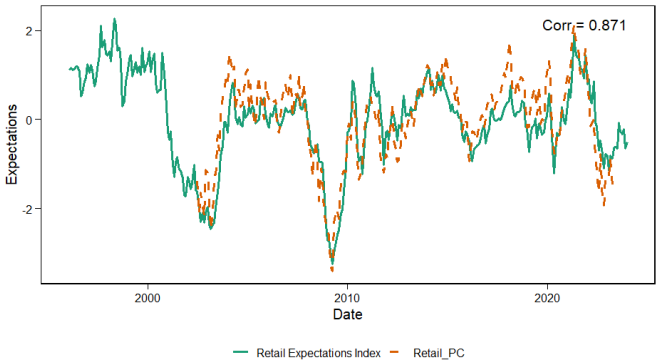
Yu, J., and Yuan, Y. (2011). Investor sentiment and the mean–variance relation. *Journal of Financial Economics*, *100*(2), 367–381. https://doi.org/10.1016/j.jfineco.2010.12.001

Figure 1: Investor Expectations - Validation

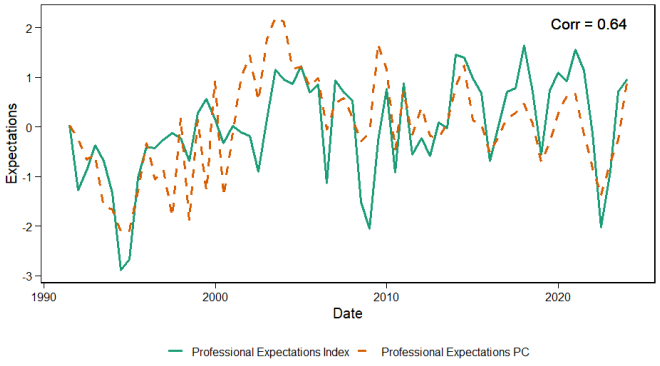
In Panel A, we overlay the time-series of our proposed retail-investor expectations index EXP^{RI} against quantitative and qualitative data on beliefs from Gallup, with the former available over the sample period 1998-2003, and the latter available to us with gaps over the sample period 1996-2015. In Panel B, we report the first principal component of EXP^{RI}, consensus probability of 1-year ahead increase in stock prices from the University of Michigan Survey, and stock market consensus expectations from the American Association of Individual Investors (AAII). In Panel C, we compare the Investor Intelligence (II) survey, which we use as our main index of professional expectations EXP^{PRO}, with the first principal component of three time-series of professionals' expectations, namely II expectations, the Livingston survey expectations, and the Shiller institutional-investor stock market confidence index. Each panel reports the relevant correlations. In Panel A, expectations are rescaled as in Greenwood and Shleifer (2014) to a decimal format. In Panels B and C, all series are standardized. The time-span in each panel differs based on data availability.



(A) EXP^{RI} and Gallup Survey Expectations



(B) EXP^{RI} and Retail Surveys PC



(C) EXP^{PRO} and Professional Surveys PC

Figure 2: Retail Investors' Stock Market Influence - Kalman Filter Results

This figure plots the 3-month moving average of the retail investor's influence on the valuation of the stock market estimated via the Kalman filter, $\hat{w}_t$ (gray), as per Section 2.3. The gray shaded area represents the 95% confidence interval around the filtered states, where the standard errors around the weights follow from our bootstrapping procedure as described in Appendix A.3. The figure also reports the time-series of direct ownership of the stock market by the Household Sector from administrative data, w_t^{FoF} (blue dotted).

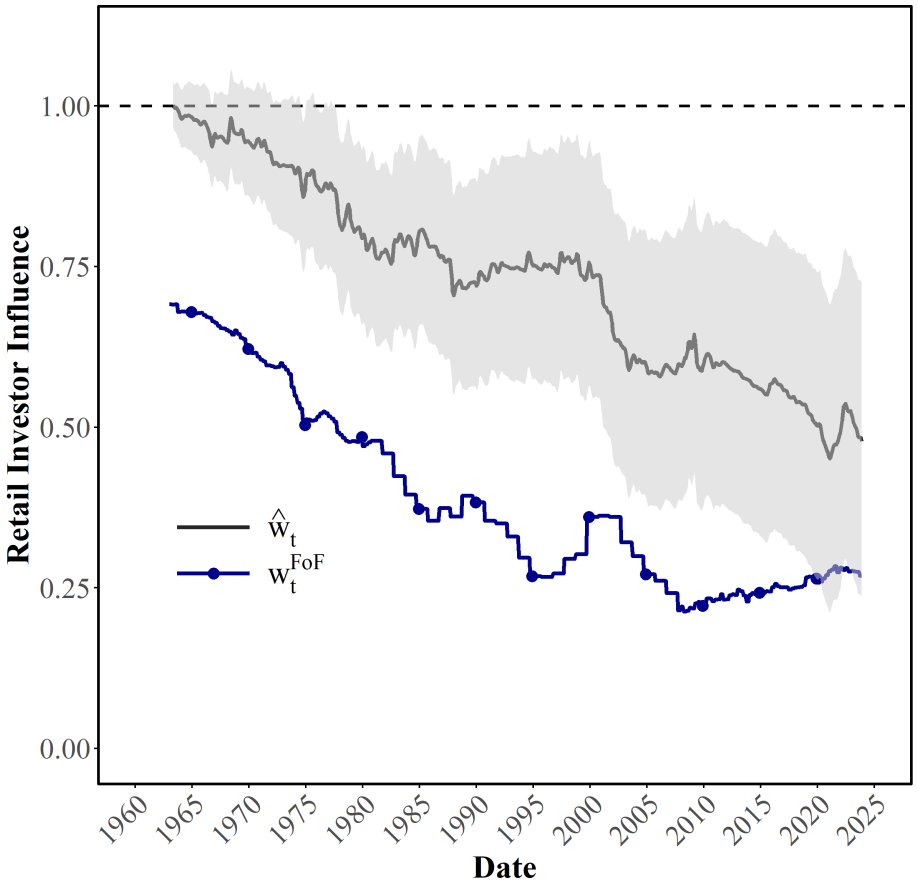
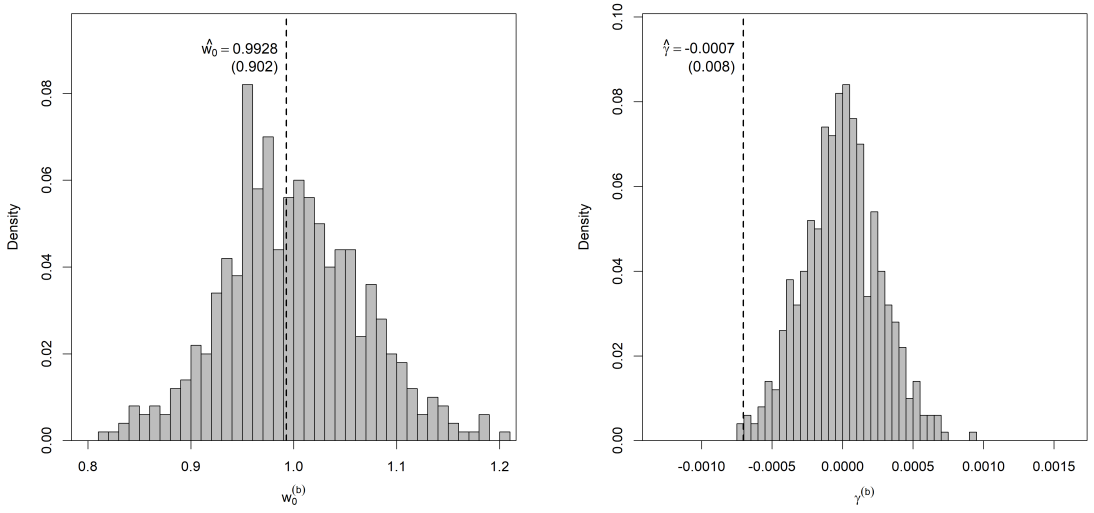
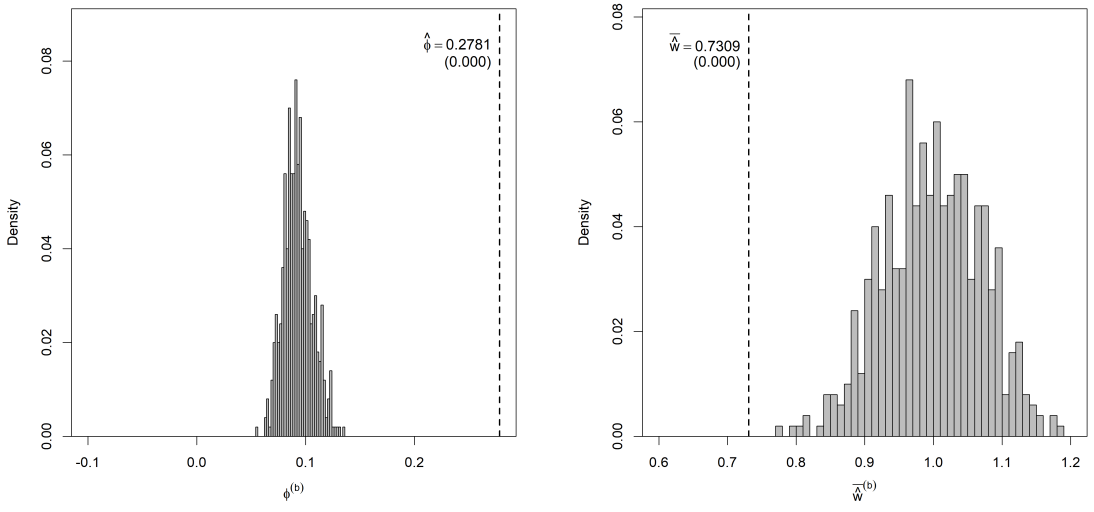


Figure 3: Retail Investors' Stock Market Influence - Hypothesis Testing

This figure reports bootstrap distributions for key parameters and quantities of interest under the null of no intermediary influence on asset prices. Specifically. we generate 500 block-bootstrapped time series of the dividend-price ratio by resampling blocks of measurement-equation residuals with replacement. Panels A to C show the distributions of the parameter estimates when the dividend-price ratio is simulated under the joint null $w_0 = 1$, $\gamma = 0$, and $\phi = 0$. Panel D shows the distribution of the sample-average estimated weight across bootstrap samples and compares it with the average weight estimated from the actual data. Each panel also marks the corresponding Kalman filter estimate from the data with a vertical dashed line. Two-sided p-values, reported in parentheses, are computed empirically from the bootstrap distribution as described in Appendix A.3.



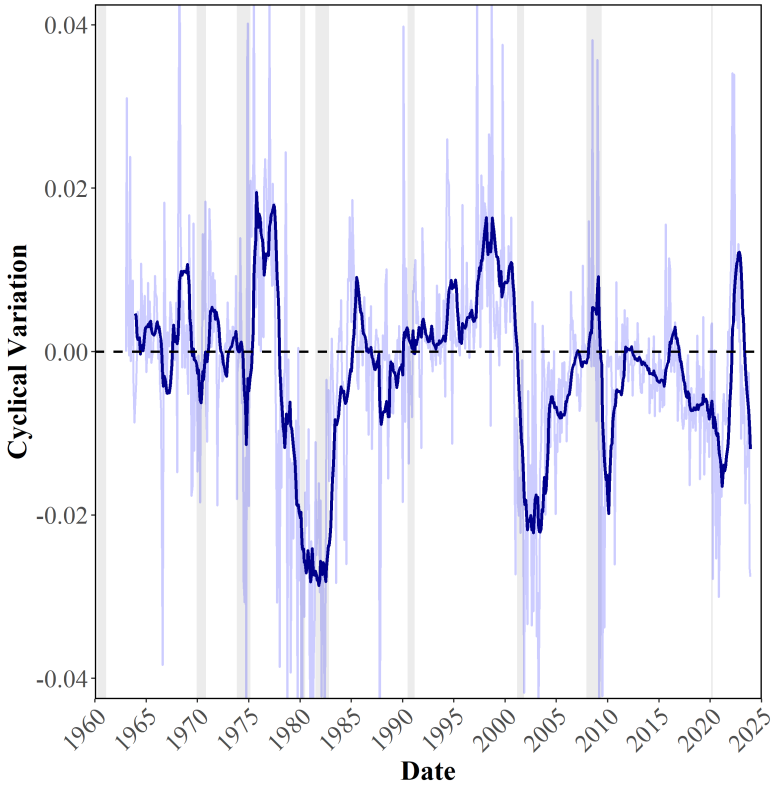
(A) w_0 **(B)** γ



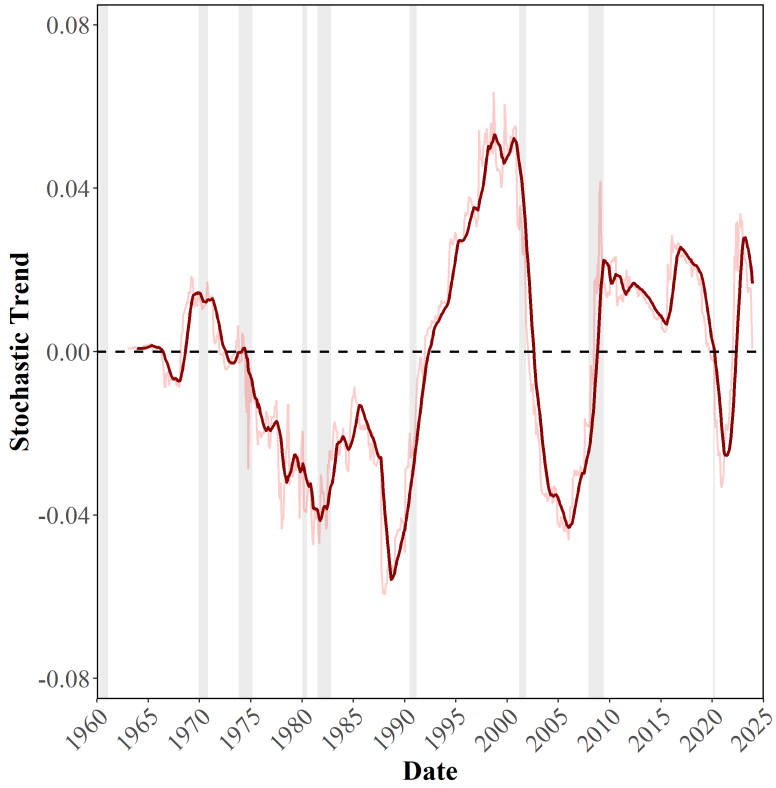
(C) ϕ **(D)** $\overline{\hat{w}}$

Figure 4: Decomposing Retail Investor Influence

This figure visualizes the transitory and permanent shocks to the retail investor influence. Panel A plots the transitory cyclical component $\hat{u}_t$ of the estimated weights from our Kalman filter. Panel B plots the stochastic trend component; $\tilde{\tau}$. The lighter colored series are taken directly from the raw data, whereas the solid lines represent their 12-month rolling averages. The light grey shaded areas correspond to NBER recession periods.



(A) $\hat{u}_t$



(B) $\tilde{\tau}_t$

Figure 5: Explaining The Cycle in Retail Investor Influence

This figure contrasts the estimated cycle component $\hat{u}_t$ obtained from the Kalman filter in Section 2.3 against several important explanatory variables from the test conducted in Table 6. When one such variable displays non-stationarity as per a Dickey–Fuller test, we consider 12-month differences. Continuous variables are standardized to have zero mean and unit standard deviation, and reported as one-year moving averages. Where applicable, we also report the pairwise correlation between $\hat{u}_t$ and the explanatory variable under consideration. For the dichotomous variables we shade the months for which we observe a value of one.

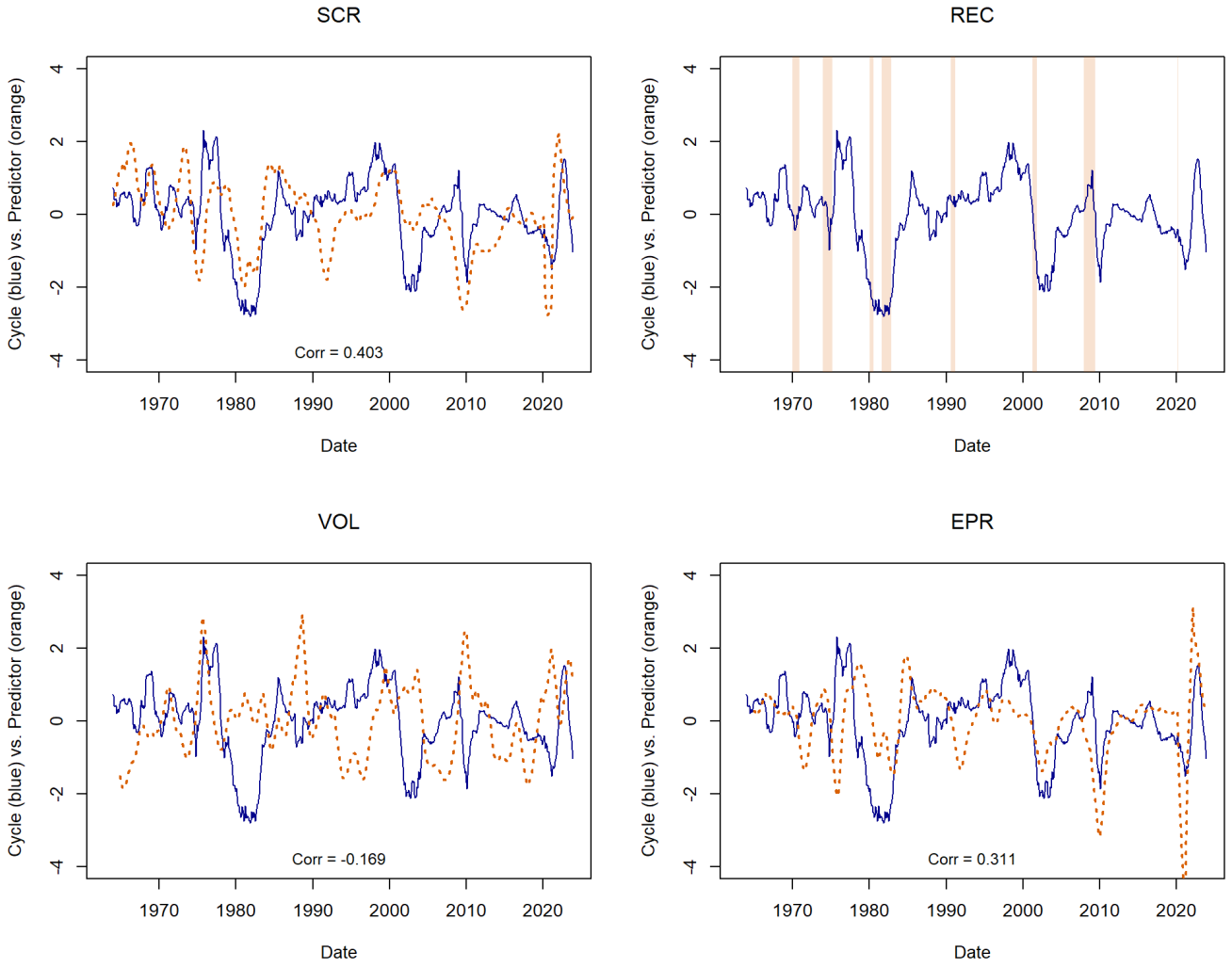
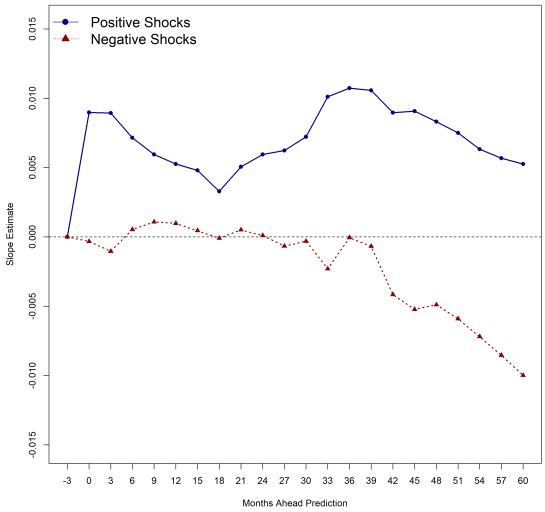
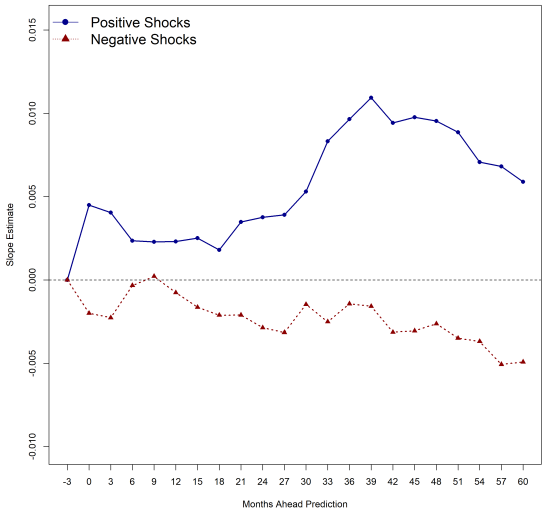


Figure 6: Predicting Long-Run Trends in Retail Investor Influence: Event Analysis

This figure shows regression output from a local-projections estimation exercise as described in Jordà (2005). The graphs present slope estimates from regressions of the future value of the stochastic trend component of retail investors' influence, $\tilde{\tau}$, on event dummies signaling the occurrence of events pre-classified as positive (blue) or a negative (red) shocks to retail investor influence. In Panel A, events and their expected directional impact on household influence classified encoded manually. In Panel B the classification is performed by an LLM, specifically OpenAI GPT o4-mini. The negative prediction horizon of -3 entry represents the starting point of the graph (no estimation).



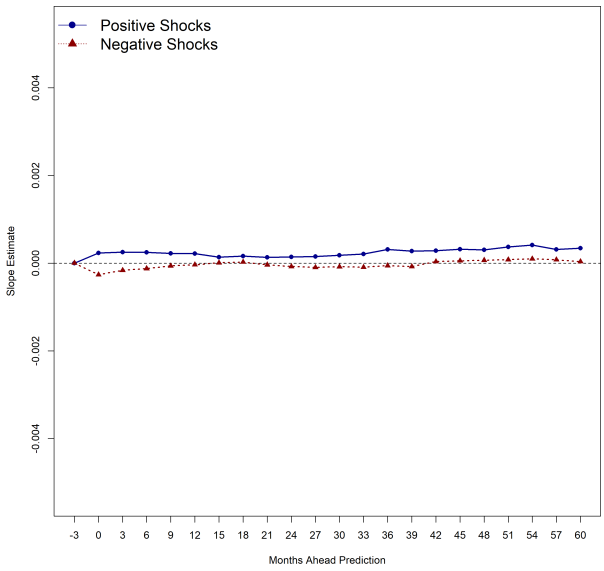
(A) Manual Classification



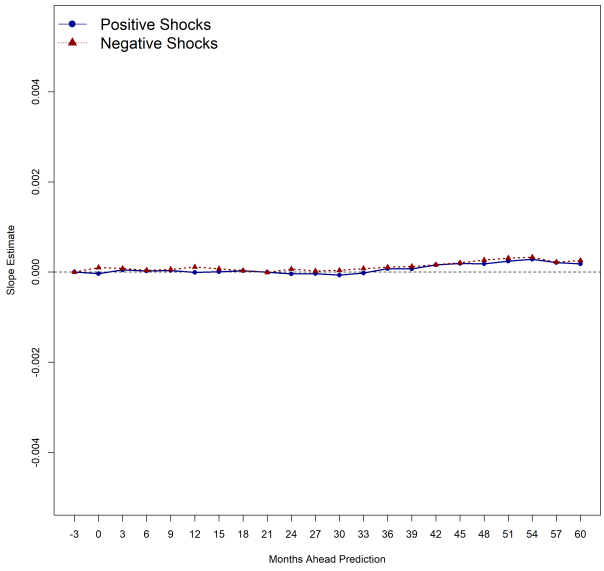
(B) LLM-based Classification

Figure 7: Predicting Long-Run Trends in Retail Investor Influence - Placebo Analysis

This figure plots results from a placebo test. In the test, we create 1000 sets of event dates. In each of these sets, the number of positive and negative shocks is the same as in our manual classification (Panel A) or the OpenAI o4-mini classification (Panel B), but the date of each event is randomized throughout the sample. We then repeat the analysis of Figure 6 involving local projections estimation (Jordà, 2005), but use the randomized event sets instead of actual event dates. The graphs report the average slope estimates across all the placebo sets of event dates.



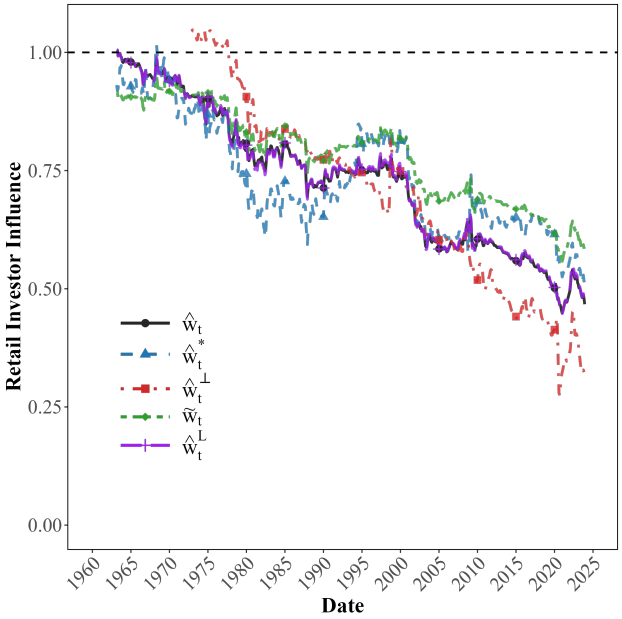
(A) Manual Classification



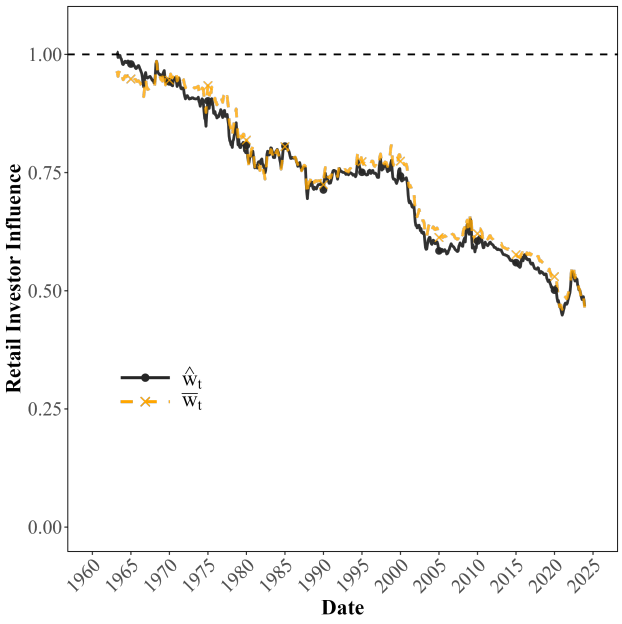
(B) LLM-based Classification

Figure 8: Retail Investors' Stock Market Influence - Kalman Filter Results with Alternative Estimation Choices

This figure shows 3-month rolling averages of the Kalman filtered estimates for the latent influence of retail investors on market valuations, under different estimation strategies. $\hat{w}_t$ (black) is the filtered weight from our main analysis. As described in Appendix D, $\hat{w}_t^*$ (blue) and $\hat{w}_t^\perp$ (red) are, compared to the baseline model, estimated with an adjusted measurement equation, whereas $\tilde{w}_t$ (green) excludes the deterministic part for the trend state-space model but leaves the measurement unaltered. $\hat{w}_t^L$ repeats the baseline estimation with a larger optimization grid (purple). The aforementioned series are presented in Panel A, whereas Panel B compares our baseline weight to the simple monthly average across the same set of weights, $\overline{w}_t$ (orange). Correlations and parameter estimates can be found in Figure D.1 and Table D.1, respectively. For additional details we refer to Appendix D.



(A) Baseline and Alternative Weight Estimates



(B) Baseline and Alternative Weights Ensemble

Figure 9: Estimating Retail Investor Influence Under Institutional Irrelevances: Simulation Results

We conduct simulations to assess how our Kalman-filtering approach performs under the null of institutional irrelevance, i.e., when only retail investors' expectations matter for asset prices. Specifically, for each simulation s we generate a time-series of the dividend–price ratio of the market where the retail investor weight is $w_t = 1 \, \forall t$. The dashed horizontal line captures this assumed weight. The figure shows results obtained from 250 simulations, where we use our Kalman-filtering approach based on the simulated dividend–price to recover a time-series $w_t^{(s)}$ of retail investor influence in each simulation s. In the figure, the average $w_t^{(s)}$ obtained across simulations is reported in bold gray line, and the gray shaded area portrays the 95% confidence intervals obtained from the empirical distribution of $w_t^{(s)}$ across-simulations at each point in time. Weights are smoothed to a 12-month average. Details on the simulations, as well as parameter estimates obtained from the simulations are presented in the Appendix, Section E.

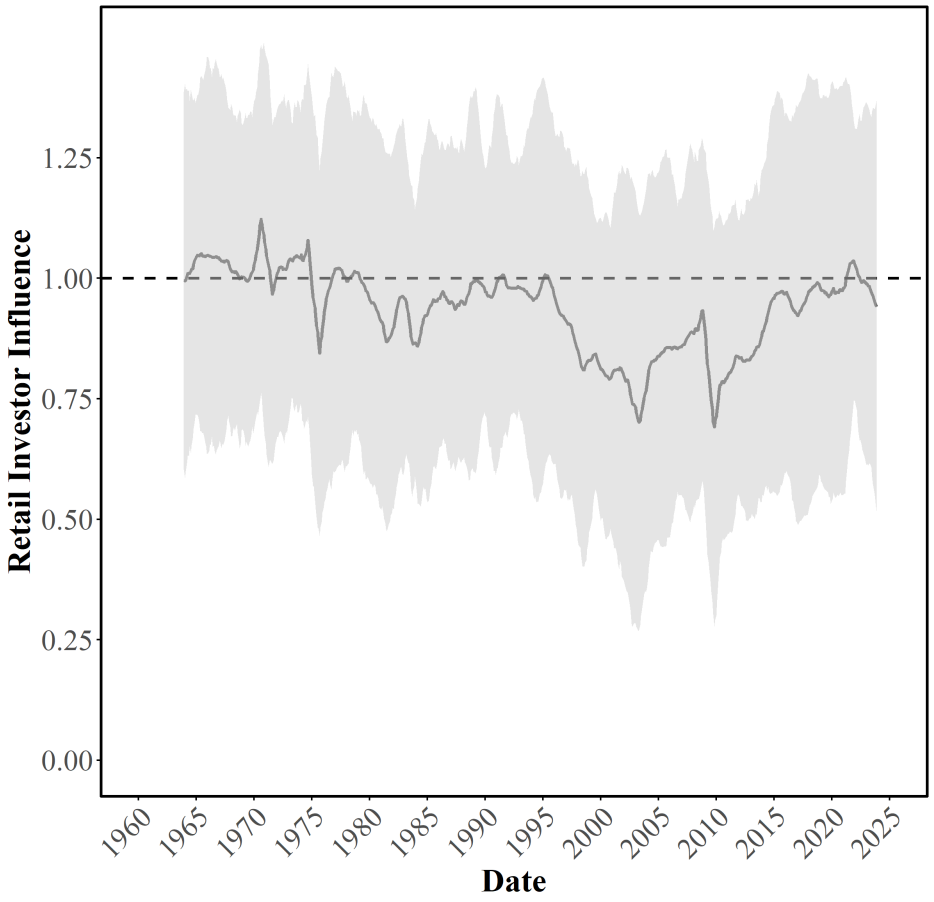


Figure 10: Estimating Retail Investors' Influence with Noisy Expectations: Simulation Results

We conduct simulations in which the dividend–price ratio of the market is driven by latent expectations processes, and the expectations we use in the Kalman filter to recover the time-series of investor influence w_t are noisy measures of such latent processes. Noise in expectations and its covariance across expectations time-series is calibrated from the data. Similarly, the dividend–price ratio generated as part of each simulation is calibrated to retain its properties in the data, and based on the assumption that only retail investor expectations have impact on asset prices, i.e., we set $w_t = 1 \, \forall t$. This figure shows results obtained from the simulations, where we use our Kalman-filtering approach based on the simulated dividend–price and the simulated noisy expectations to recover a time-series $w_t^{(s)}$ of retail investor influence in each simulation s. In the figure, the average $w_t^{(s)}$ obtained across simulations is reported in bold gray line, and the gray shaded area portrays the 95% confidence intervals obtained from the empirical distribution of $w_t^{(s)}$ across-simulations at each point in time. Weights are smoothed to a 12-month average. Details on the simulations, as well as parameter estimates obtained from the simulations are presented in the Appendix, Section F.

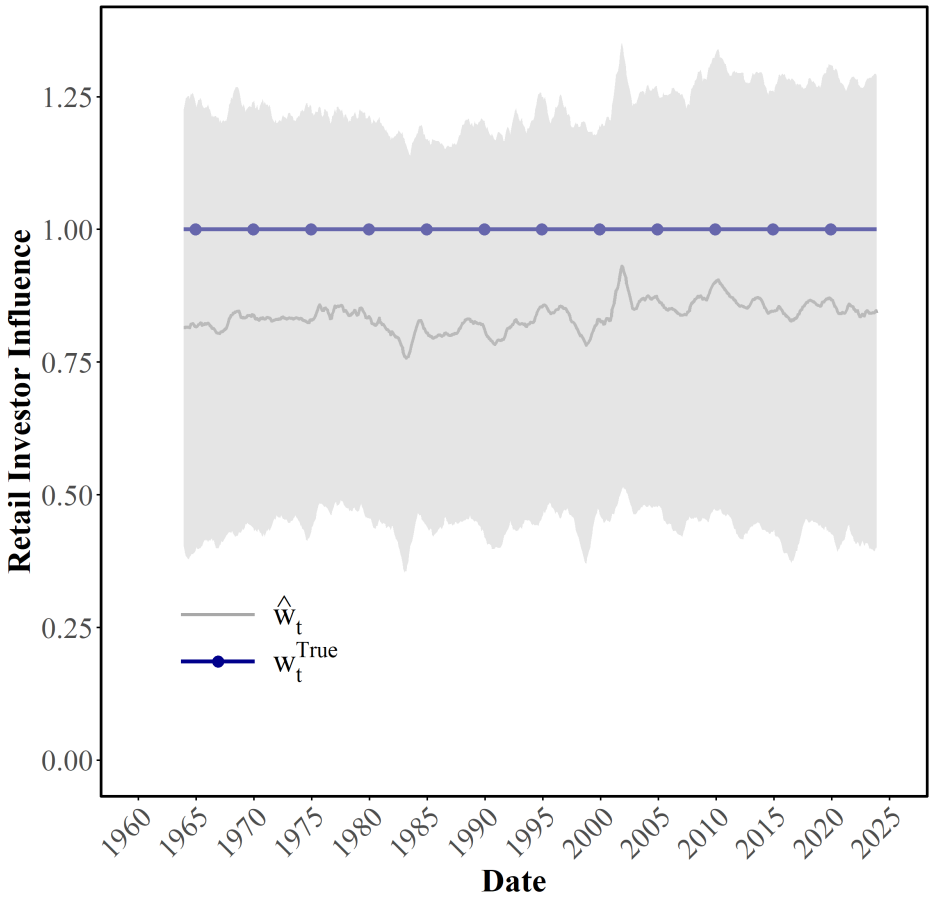


Table 1: Retail Investors: Belief Formation by Age Group

g	(1)	(2)	(3)	(4)	(5)
Age range	25 to 34	35 to 44	45 to 54	55 to 64	65 to 75
a_g	0.118	0.099	0.092	0.087	0.049
	[28.94]	[33.05]	[45.75]	[32.18]	[2.97]
b_g	0.227	0.264	0.255	0.259	0.289
	[12.10]	[23.27]	[27.42]	[19.69]	[3.23]
λ_g	0.292	0.458	0.453	0.496	0.768
	[4.03]	[12.67]	[18.82]	[16.01]	[8.20]
R^2	62.07	85.11	83.74	73.89	53.60

Using Gallup data on retail investors' quantitative expectations of future 1-year stock market returns, we estimate the following cross-sectional regression:

$$EXP_{g,t}^{RI} = a_g + b_g \sum_{j=1}^{15} w_{g,j} R_{t-j+1}, \qquad w_{g,j} = \frac{\lambda_g^{j-1}}{\sum_{k=1}^{15} \lambda_g^{k-1}},$$

where $EXP_{g,t}^{RI}$ is the group-specific average expectation of future 1-year stock returns on the aggregate stock market at time t, and R_{tj} is the stock market return, from CRSP, realized j years before. The table reports the estimated coefficients a_g, b_g, λ_g for each age group g. Newey-West T-statistics are reported in brackets. Sample period is 2000:01 to 2003:04, in which the survey collected quantitative expectations data from its participants.

Table 2: Expectations and Flows

	Panel A: Flows into Equity Mutual Funds					Panel B: Flows into Separate Accounts				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
EXP^{PRO}	0.117		0.040	0.011	0.076	0.606		0.512	0.489	0.431
	[1.39]		[0.48]	[0.16]	[0.79]	[2.01]		[1.98]	[1.91]	[1.73]
	(0.168)		(0.634)	(0.877)	(0.431)	(0.047)		(0.051)	(0.056)	(0.083)
	(0.084)		(0.317)	(0.438)	(0.216)	(0.024)		(0.026)	(0.028)	(0.041)
EXP^{RI}		0.365	0.341	0.347	0.292		0.466	0.198	0.176	0.141
		[2.28]	[2.08]	[2.04]	[1.99]		[1.43]	[0.61]	[0.56]	[0.45]
		(0.024)	(0.040)	(0.043)	(0.048)		(0.155)	(0.311)	(0.316)	(0.332)
		(0.012)	(0.020)	(0.022)	(0.024)		(0.077)	(0.156)	(0.158)	(0.166)
Adj. R^2	0.00	0.03	0.02	0.49	0.60	0.04	0.06	0.02	0.45	0.55
Observations	136	136	136	136	136	120	120	120	120	120
Controls										
Trend	N	N	N	Y	Y	N	N	N	Y	Y
Lagged Flows	N	N	N	N	Y	N	N	N	N	Y
Returns	N	N	N	N	Y	N	N	N	N	Y

In Panel A we regress quarterly percentage flows into equity mutual fund on changes in investor expectations. Columns (1) and (2) present the result of the univariate analysis; column (3) allows to gauge the explanatory power of retail investor expectations for flows after controlling for professional investor expectations. Columns (4) to (6) augment the bivariate regressions with controls including a deterministic trend, lag flows, and lag market returns, as indicated. Panel B repeats the analysis, but focuses on flows into separate accounts. Newey-West t-statistics based on Newey and West (1994) lag selection, are reported in brackets. Both two-sided and one-sided p-values of the alternative hypothesis of a positive relation between expectations and flows, are reported. The sample period is 1990:Q4 to 2023:Q4 for equity mutual funds, and 1994:Q4 for separate account data.

Table 3: Summary Statistics

Variable	Mean	Std	Min	Max	Periodicity	Obs	Sample	Source	Description
Panel A: Main Variables									
D/P	0.028	0.012	0.011	0.064	Monthly	732.00	1963 - 2023	Goyal and Welch (2008)	Dividend-price ratio
EXP^{RI}	0.111	0.021	0.036	0.181	Monthly	732.00	1963 - 2023	Self-Constructed	Aggregate expectations held by retail investors
EXP^{PRO}	0.102	0.030	0.010	0.182	Monthly	732.00	1963 - 2023	Self-Constructed	Aggregate expectations held by professional investors
w^{FoF}	0.388	0.145	0.213	0.691	Quarterly	244	1963 - 2023	Self-Constructed	Weight based on Flow-of-Funds data
Panel B: Other Variables									
DTI	0.161	0.011	0.124	0.182	Quarterly	175	1980 - 2023	FRED	Household financial obligations as a fraction of disposable personal income
PFDET	0.319	0.161	0.106	1.034	Monthly	552	1978 - 2023	UMICH	Constructed from Table 6 of the Survey of Consumers, PFDET represents the fraction of respondents rating their financial situation as worse compared to one year ago
PDI	0.433	0.512	0.016	2.198	Monthly	732	1963 - 2023	FRED	Personal dividend income (trillions of USD)
SCR	0.016	0.014	-0.155	0.054	Monthly	732	1963 - 2023	Cochrane (2017)	Surplus Consumption Ratio
ICR	0.063	0.022	0.022	0.134	Monthly	648	1970 - 2023	He et al. (2017)	Intermediary Capital Ratio
LEV	0.048	0.026	0.006	0.107	Quarterly	199	1968 - 2017	Adrian et al. (2014)	Broker-Dealer Leverage
EPR	0.600	0.025	0.512	0.647	Monthly	732	1963 - 2023	FRED	Employment-population ratio
ETA	0.243	0.087	0.095	0.424	Quarterly	244	1963 - 2023	FRED	Household corporate equity holdings as a fraction of total financial assets
RET	0.009	0.043	-0.216	0.168	Monthly	732	1963 - 2023	CRSP	Item "VWRETD": the monthly value-weighted return on the value-weighted market portfolio of US equities, including all distributions

This table shows summary statistics for the variables used in our empirical design. For details on the series that are not self-constructed, we refer to the original papers presented in the "Source" column.

Table 4: Kalman Filter - Initialization

Par.	Description	Initial Value/Guess	Motivation
β	Scaling factor linking return expectations and dp	-0.536	From a regression of dp on a weighted sum of survey -based investor expectations, where weights are from administrative data on stock ownership by the Household Sector from the Federal Reserve.
w_0	Influence or retail investors at sample start	1.000	Set to 1; consistent with no role for professionals.
τ_0	Trend component of retail investors' influence at sample start	0.000	Set to 0, so w_0 easily maps on w_t at the beginning of the sample.
u_0	Demeaned cyclical component of the retail investor weight	0.000	u_t is assumed to be at the long-run mean at the beginning of the sample.
μ_0	Demeaned discount-rate process at the beginning of time	0.000	μ_t is assumed to be at the long-run mean at the beginning of time.
γ	Deterministic drift in τ_t	0.000	We take no stance on the sign of the drift.
ϕ	Persistence of cyclical component u_t	0.900	To capture high persistence in households' participation in stocks, while allowing for a stationary process.
ρ	Persistence of μ_t	0.932	Based on estimates in Van Binsbergen and Koijen (2010).
σ_ε^2	Variance of innovations in the measurement equation	$\{0.010, ..., R^{max}\}$	A range of possible values is considered as part of the Kalman filter optimization procedure. Grid contains 10 evenly spaced points. More details are in the Appendix A.2.1.
σ_η^2	Variance of transitory shocks in w_t	$\{0.25, 0.5, 1, 2, ..., v\} \times \sigma_\varepsilon^2$	Set to a multiple of σ_ε^2 for the Kalman filter optimization routine, with $v = \left\lfloor \frac{1}{R^{\max}} \right\rfloor = 5$. Grid contains 7 points, so total search is over 70 $(\sigma_\varepsilon^2, \sigma_\eta^2)$ combinations.
σ_ζ^2	Variance of innovations in τ_t	5×10^{-4}	Calibrated and fixed to reduce the likelihood that w_t falls outside of the interval [0,1]. More details are in the Appendix A.2.
σ_ξ^2	Variance of innovations in μ_t	0.023	Calibrated and fixed to match the variance of discount-rate shocks from Van Binsbergen and Koijen (2010), while allowing for a unit loading of μ_t on the dividend-price ratio. More details are in the Appendix A.2.
$P_{0\|0}^{(1,1)}$	Initial uncertainty for τ_0	0	No uncertainty on τ_0, such that w_0 pins down the initial level of w_t.
$P_{0\|0}^{(2,2)}$	Initial uncertainty for u_0	0.250	Based on feasible range of the weights as described in Schneider and Georgakis (2013): $((0.500 \times (max(w_t) - min(w_t)))^2 = 0.250$.
$P_{0\|0}^{(3,3)}$	Initial uncertainty for μ_0	0.175	Set to long-run variance of the process, $\frac{\sigma_\xi^2}{(1-\rho^2)}$ based on estimates in Van Binsbergen and Koijen (2010).

This table shows the initialization strategy for the variables that enter into the Kalman filter estimation procedure.

Table 5: Kalman Filter - Estimation Results

Par.	Kalman Filter	Bootstrapped Distribution				
	Estimates	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
β	-0.5840	-0.8889	-0.7731	-0.6724	-0.5540	-0.4599
w_0	0.9928	0.9195	0.9585	0.9962	1.0379	1.0685
γ	-0.0007	-0.0012	-0.0009	-0.0007	-0.0005	-0.0003
ϕ	0.2781	0.2752	0.2789	0.2823	0.2854	0.2893
ρ	0.9530	0.7859	0.8291	0.8634	0.8898	0.9054
σ_ε^2	0.0652	0.0651	0.0652	0.0653	0.0655	0.0658
σ_η^2	0.1312	0.1244	0.1271	0.1298	0.1330	0.1353

This table shows the Kalman filter parameter estimates obtained for the model in Section 2.3 using the estimation procedure outlined therein and further explained in Section A.2. The table also shows the bootstrapped distribution of the parameter estimates obtained across 500 bootstrap samples. The bootstrapping procedure is performed using the estimates from the second column to simulate measurements as per Appendix A.3, Eq. (A.17). The table omits reporting model parameters that are fixed, as detailed in Section 2.3.

Table 6: Explaining Cyclical Variation in Retail Investor Influence

$(h=1)$	Panel A: Risk and Risk Preferences					Panel B: Household Finances					Panel C: Attention					
SCR	0.247					DTI	0.076					$TRET_{20}^{Q}$	-0.193			
	[3.52]						[1.65]						[-1.23]			
REC		-0.546				EPR		0.093				$TRET_{10}^{Q}$		-0.032		
		[-2.23]						[2.58]						[-0.14]		
VOL			-0.134			PFDET			-0.016			$TRET_{20}^{Y}$			0.189		
			[-1.70]						[-0.40]						[1.05]	
ICR				0.027		PDI				-0.008		$TRET_{10}^{Y}$				0.329	
				[0.52]						[-0.29]						[1.31]	
LEV					0.017	ETA					0.014	$POSRET^{Y}$					0.164
					[0.44]						[0.23]						[0.93]
Adj.R^2	5.95	2.93	1.65	-0.08	-0.14		0.46	0.72	-0.16	-0.13	-0.12		0.46	-0.13	0.46	0.96	0.31
Observations	732	732	721	647	594		522	731	551	731	729		732	732	732	732	732

$(h=12)$	Panel D: Risk and Risk Preferences					Panel E: Household Finances					Panel F: Attention					
SCR	0.291					DTI	0.079					$TRET_{20}^{Q}$	-0.347			
	[2.74]						[1.18]						[-2.09]			
REC		-0.682				EPR		0.236				$TRET_{10}^{Q}$		0.058		
		[-2.14]						[2.59]						[0.29]		
VOL			-0.144			PFDET			0.124			$TRET_{20}^{Y}$			0.058		
			[-1.96]						[1.52]						[0.25]	
ICR				0.080		PDI				-0.042		$TRET_{10}^{Y}$				0.294	
				[0.89]						[-0.55]						[0.95]	
LEV					-0.054	ETA					0.054	$POSRET^{Y}$					-0.021
					[-0.63]						[0.59]						[-0.09]
Adj.R^2	8.47	4.71	1.93	0.44	0.10		0.70	5.42	1.28	0.04	0.15		1.82	-0.11	-0.08	0.75	-0.13
Observations	721	721	721	636	585		489	720	540	720	720		721	721	721	721	721

Panels A to C of this table show regressions of the estimated cyclical component of retail investors' influence, $\hat{u}_t$, on different sets of explanatory variables. We consider three sets of of such variables: (i) Risk and Risk Preferences, measured via Campbell and Cochrane surplus consumption ratio (SCR), a dummy variable for recessions (REC), intermediary capital ratio (ICR), and Intermediary leverage (LEV), and 12-month trailing volatility (VOL); (ii) Household-finance variables, measured via Households' debt to income ratio (DTI), Households' equity share of financial assets (ETA), Households' beliefs about their financial condition deteriorating (PFDET), and personal dividend income (PDI); (iii) Market-based drivers of attention; these are $TRET_{20}^{Q}$ ($TRET_{20}^{Y}$), a dummy variable that is equal to one when recent quarterly (yearly) returns are in the top quintile of the distribution, $TRET_{10}^{Q}$ ($TRET_{10}^{Y}$), a dummy that is equal to one when recent quarterly (yearly) returns are in the top decile of the distribution, $POSRET^{Y}$, a dummy variable that is equal to 1 when market returns are positive in the current month, and POS^{Y}, a dummy that is equal to one when yearly returns are positive. Panels D to F repeat the analysis, but use a smooth 12-month moving average of $\hat{u}_t$. All continuous explanatory variables that display non-stationary behavior via a Dickey–Fuller test, and converted to one-month (twelve-month) differences in the top (bottom) panels. Newey-West t-statistics based on Newey and West (1994) lag selection, are reported in brackets. The estimates for the intercept are omitted for brevity.

Table 7: Long-Run Patterns in Retail Investor Influence: Event Analysis

Panel A: Manual Classification					Panel B: Reasoning LLM Classification				
	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
Positive Shock	0.006		0.005	0.005	Positive Shock	0.006		0.006	0.006
	[1.26]		[1.16]	[1.08]		[1.88]		[1.81]	[1.97]
	(0.209)		(0.246)	(0.283)		(0.060)		(0.071)	(0.049)
	(0.105)		(0.123)	(0.141)		(0.030)		(0.036)	(0.024)
Negative Shock		-0.010	-0.010	-0.010	Negative Shock		-0.005	-0.005	-0.005
		[-2.37]	[-2.32]	[-2.18]			[-1.27]	[-1.19]	[-1.21]
		(0.018)	(0.021)	(0.030)			(0.204)	(0.233)	(0.228)
		(0.009)	(0.010)	(0.015)			(0.102)	(0.117)	(0.114)
Δ			0.015	0.015	Δ			0.011	0.011
			(0.021)	(0.026)				(0.041)	(0.028)
R^2	0.002	0.006	0.008	0.010	R^2	0.003	0.002	0.004	0.011
Observations	672	672	672	672	Observations	672	672	672	672

We predict the 5-year ahead stochastic component of the trend in retail investor influence, $\tilde{\tau}$ using historical events. We partition these events, which are listed in Table C.1 of the Appendix, into two main categories of interest: (i) events that constitute a positive shock to investor influence; (ii) events that constitute a negative shock to investor influence. The classification of these events is performed in two ways: manually (Panel A), and using an LLM with reasoning capabilities (GPT 4o-mini, Panel B). In each panel. we use the event classification to create a "Positive Shock" dummy and a "Negative Shock" dummy. We use these dummies as predictors of the future long-run behavior of retail investors' influence. If multiple events occur at the same point in time, we take the majority vote across events in terms of the assumed shock direction. Columns (1) and (2) present the results of univariate regressions. Column (3) presents the results of bivariate regressions, and column (4) repeats the regression while controlling for the occurrence of events that are flagged as ambiguous by the corresponding classification method. Below each coefficient estimate we also report: (i) Newey-West t-statistics based on Newey and West (1994) lag selection; (ii) a two-sided p-value; (iii) a one-sided p-value. This one-sided p-value tests whether positive shocks lead to a higher future value of retail investors' influence, and whether negative shocks lead to a lower value of retail investors' influence. In the last two columns of each panel, we also present the difference between the two coefficient estimates, alongside its two-sided p-value testing whether positive and negative shocks have the same impact for future long-run retail investor influence. The model intercept is omitted from the table for brevity.

Appendix

Contents of the Appendix

A Kalman-Filter Estimation: Additional Information **57**

A.1 Equations and Objective Function 57

A.2 Initialization and Optimization 59

A.2.1 Initialization: Additional Details 59

A.2.2 Estimation Strategy 60

A.2.3 Optimizing the Kalman Filter 61

A.3 Confidence Intervals and Hypothesis Testing: Bootstrapping Approach . . . 64

B Households' Stock Market Direct Ownership: Estimates from Administrative Data **66**

C The Determinants of Long-Run Variation in Retail Investor Influence: Event Classification assisted by an LLM **68**

C.1 Prompts 68

C.2 LLM Events 71

D Estimating Retail Investor Influence with Alternative Model Specifications **83**

E Estimating Investor Influence when Institutions are Irrelevant: Simulation Analysis **87**

F Estimating Investor Influence with Noisy Expectations: Simulation Analysis **89**

A Kalman-Filter Estimation: Additional Information

A.1 Equations and Objective Function

Consider the Kalman filter framework as described in Section 2.2:

$$\dot{dp}_t = \dot{H}_t x_t + \varepsilon_t$$

$$x_t = F x_{t-1} + c + G\Sigma_t$$

, with

$$x_t = \begin{bmatrix} \tau_t \\ u_t \\ \mu_t \end{bmatrix} \quad ; \quad F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \phi & 0 \\ 0 & 0 & \rho \end{bmatrix} \quad ; \quad c = \begin{bmatrix} \gamma \\ 0 \\ 0 \end{bmatrix},$$

$$G = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad ; \quad \Sigma_t = \begin{bmatrix} \zeta_t \\ \eta_t \\ \xi_t \end{bmatrix},$$

and

$$\Sigma_t \overset{\text{iid}}{\sim} \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, Q \right) \quad ; \quad Q = \begin{bmatrix} \sigma_\zeta^2 & 0 & 0 \\ 0 & \sigma_\eta^2 & 0 \\ 0 & 0 & \sigma_\xi^2 \end{bmatrix}.$$

To estimate the states and parameters that give the optimal predictions for the measurement, the Kalman procedure is as follows. First, we get a prediction step for the states coming from the physical model:

$$\hat{x}_{t|t-1} = F\hat{x}_{t-1|t-1} + \hat{c} \tag{A.1}$$

as well as a prediction for the state covariance P:

$$P_{t|t-1} = F P_{t-1|t-1} F^\intercal + Q. \tag{A.2}$$

, which is initialized as a diagonal matrix at the beginning of time ($P_{0|0}$, details in Table 4). Using the predicted state, the Kalman filter proceeds into an update step where it computes the innovation with respect to the true measurement:

$$e_t = \dot{dp}_t - \dot{H}_t \hat{x}_{t|t-1} \tag{A.3}$$

and the covariance matrix of the innovations;

$$S_t = \dot{H}_t P_{t|t-1} \dot{H}_t^\intercal + \sigma_\varepsilon^2. \tag{A.4}$$

Then, the Kalman Gain is calculated to find the extent to which the KF relies on the measurement versus the prior estimate:

$$K_t = P_{t|t-1} \dot{H}_t^\intercal S_t^{-1}. \tag{A.5}$$

Finally, having obtained K_t, the filter makes the revised prediction for the latent states:

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t e_t \tag{A.6}$$

, and it updates the estimate for the state covariance:

$$P_{t|t} = (I - K_t \dot{H}_t) P_{t|t-1}. \tag{A.7}$$

Finally, the log-likelihood is evaluated recursively using the Kalman filter;

$$\mathcal{L}(\theta) = -\frac{1}{2} \sum_{t=1}^{T} \left[\log(2\pi) + \log(S_t) + \frac{e_t^2}{S_t} \right] \tag{A.8}$$

, where $\theta = [\theta_p, \theta_V]$, and the objective is to maximize with respect to the parameter vector of interest: $\theta_p = [\beta, w_0, \gamma, \phi, \rho]$[1] for some selection of $\theta_V = \left[\sigma_\varepsilon^2, \sigma_\zeta^2, \sigma_\eta^2, \sigma_\xi^2\right]$.

[1]Note that the scaling factor β enters into $\dot{H}_t$, as explained in Section 2.3.

A.2 Initialization and Optimization

A.2.1 Initialization: Additional Details

To implement the Kalman-filtering procedure described in Section 2.2, we have to select starting values for all variables that enter the model, and make initial guesses for the parameters of interest. While the list of all choices and the corresponding rationale is presented in Table 4, of the paper, here we provide some additional details on a selected set of such choices.

Scaling parameter β: This parameter is the loading of aggregate (i.e., weighted) return expectations on the log dividend-price ratio. To obtain a guess for this parameter, we regress the dividend-price ratio on a weighted sum of expectations. While intuitive, this step requires to form a meaningful weighted sum, and this is challenging since we treat expectations weights as unobserved. To make progress, we rely on administrative Flow-of-Funds data from the Financial Accounts of the United States, that has been used in prior work to describe patterns of delegation in the US stock market. Using this data, as well as estimates from earlier work (French, 2008), we construct a time-series of households' direct ownership share of stocks that spans the sample period of interest (1963-01, 2023-12). We then use this time-series to obtain an initial guess for β.[2]

Variance of permanent shocks, σ^2_ζ: In our estimation, there is nothing explicitly preventing the filtered time-series w_t to fall outside of the range $[0, 1]$. At the same time, to the extent that this time-series is in this interval, it is easier to interpret the weighted sum of subjective expectations that we form as the belief of a representative investor in the marketplace. Such an investor holds the entire market in equilibrium, so that their "weight" in the market is 1, as opposed to the weight of a very small investor whose beliefs are irrelevant for price formation.

When thinking about how to select σ^2_ζ, we realize that selecting a high a value of this parameter would result in a large probability that the recovered time-series of w_t reaches outside of the aforementioned interval, and by the unit-root property of τ, it stays outside of the interval for a long time. So, we select a value of this variance that instead helps estimate a time-series of w_t that is easier to interpret. To that end, this variance is computed as $\sigma^2_\zeta = \frac{w_0}{[\Phi^{-1}(0.95)]^2 \times T}$, with $T = 732$ months (our sample length), $w_0 = 1$ as per our choice of an initial guess for w_0, and Φ is the standard normal CDF.

[2]Importantly, this approach to initialization does not constrain parameter estimation, and the time-series of the administrative data does not enter the estimation procedure at all beyond the step described here.

A.2.2 Estimation Strategy

Having discussed the initial values for the parameters, we now turn to explaining how we estimate the model. To search for a global solution and allow for uncertainty, we estimate the Kalman filter with an iterative optimization procedure. Before going into the details, we stress that the goal of our estimation strategy is to let the data speak about what the estimate for the influence of retail investors on market valuations should be at any given point in time. So we keep the number and intensity of constraints imposed on the filtering procedure at a minimum. For this reason, the only direct optimization constraint we consider is that we require the estimates of the autoregressive parameters ϕ and ρ to be between 0 and 1, to reflect some degree of persistence in the autoregressive latent processes in our model, and thus avoid non-stationary solutions.

With the initial values and parameter constraints in place, we are able to optimize the model via a grid search over different model architectures, as discussed briefly in Section 2.3. In short, our method entails searching over a set of candidate models, in terms of signal-to-noise ratios, to reach the best global solution. To implement the procedure we start by specifying a grid for the variance of the disturbances in the measurement equation, σ_ε^2, as can be seen in Table 4. This grid considers ten different values, starting at a small variance of 0.01, up to $R^{max} \approx 0.17$ - which matches the unconditional variance of the *dp* in the data.

We follow a similar logic for the process noise of the cyclical component of the retail investor weight, σ_η^2. Given that we do not have data to inform us about the size of this error, we set its candidate values relative to the ones from the σ_ε^2 grid. This idea closely aligns with one of the fundamental steps in the Kalman filter — computing the Kalman Gain — which balances out the reliance on the measurement versus the state-space prediction based on the ratio of variances (Eq. (A.5)). We consider 7 ratios, $\sigma_\eta^2 \in \{0.25, 0.5, 1, 2, ..., v\} \times \sigma_\varepsilon^2$, where $v = \left\lfloor \frac{1}{R^{\max}} \right\rfloor = 5$, to explore an extensive set of possible solutions for the filter. Hence, interacting the grids, we obtain a total number of $7 \times 10 = 70$ different $(\sigma_\eta^2, \sigma_\varepsilon^2)$-pairs. For the process noise of discount rates we use a fixed value of $\sigma_\xi^2 = 0.023$, which we directly take from the estimates of Van Binsbergen and Koijen (2010) - leaving the grid size unaltered.[3]

In summary, the optimization procedure performs an outer loop over filtering architectures dictated by the signal-to-noise ratio in the system, which is determined by the noise vector $\theta_V = \left[\sigma_\varepsilon^2, \sigma_\zeta^2, \sigma_\eta^2, \sigma_\xi^2\right] = [R, diag(Q)]$. Given that we can fix σ_ζ^2 (see Section A.2.1) and σ_ξ^2 based on empirical estimates, the candidate (Q, R) pairs we estimate the filter for correspond to the possible $(\sigma_\eta^2, \sigma_\varepsilon^2)$-pairs we described earlier.

[3]Given that the discount rate process enters our measurement equation with unit slope, we rescale its variance using the slope estimates from Van Binsbergen and Koijen (2010) Table IA.I.; $\sigma_\xi^2 = \frac{0.016^2}{(1-0.932\times0.96)^2} = 0.023$.

A.2.3 Optimizing the Kalman Filter

After setting up the signal-to-noise (STN) grid, we can start estimating the Kalman filter for each of the $m = 1, ..., M = 70$ schemes - which can be interpreted as an *outer loop* over the filter architectures. We also consider an *inner loop* for each filter m, to iteratively optimize the scaling factor β from the measurement equation. Precisely, within each m we perform at most $J = 50$ optimization rounds over the scaling factor. The procedure is as follows.

First, for some STN scheme $\theta_V^{(m)}$, we run the Kalman filter as described in Section 2.3. This will give us an initial solution $\mathcal{S}$ at inner loop iteration $j = 1$, that contains estimates for the latent processes and the parameters of interest:

$$\mathcal{S}^{(m,1)} = \{\hat{w}_t^{(m,1)}, \hat{\theta}_p^{(m,1)}\}, \quad \text{with} \quad \hat{\theta}_p^{(m,1)} = \left[\hat{\beta}^{(m,1)}, \hat{w}_0^{(m,1)}, \hat{\gamma}^{(m,1)}, \hat{\phi}^{(m,1)}, \hat{\rho}^{(m,1)}\right],$$

where the estimate for the scaling factor is found from a regression of the dp-ratio on the estimated share of retail investors:

$$dp_t = \alpha + \beta \left[\hat{w}_t^{(m,1)} EXP_t^{RI} + (1 - \hat{w}_t^{(m,1)}) EXP_t^{PRO}\right] + \epsilon_t \tag{A.9}$$

, where

$$\hat{w}_t^{(m,1)} = \hat{w}_0^{(m,1)} + \hat{\tau}_t^{(m,1)} + \hat{u}_t^{(m,1)}$$

, and

$$\begin{aligned} \hat{\tau}_t^{(m,1)} &= \hat{\tau}_{t-1}^{(m,1)} + \hat{\gamma}, \\ \hat{u}_t^{(m,1)} &= \hat{\phi}^{(m,1)} \hat{u}_{t-1}^{(m,1)}. \end{aligned}$$

After this first iteration, we use the estimate for the scaling factor $\hat{\beta}^{(m,1)}$ to update the initial guess that we made to initialize the model (which was based on the Flow-of-Funds data). In other words, we update the guesses for $\dot{dp}_t$ and H_t, since the scaling factor is included into both of these terms in the measurement equation (Eq. (5)). We then re-run the filter — still within filter specification m — with the updated scaling factor. We repeat this for a maximum of $J = 50$ iterations, and we terminate the inner loop when the change in the scaling estimate satisfies a prespecified stopping criterion: $|\hat{\beta}^{(m,j)} - \hat{\beta}^{(m,j-1)}| < 10^{-3}$. When convergence is reached, we take the stabilized solution $\mathcal{S}^{(m,\star)}$, and extract the parameter estimates to construct the set of weights for STN scheme m.

After completing the full estimation procedure, we will have obtained a total of $M = 70$ optimized solution sets;

$$\mathcal{S}^{\star} = \{\mathcal{S}^{(1,\star)}, ..., \mathcal{S}^{(M,\star)}\}.$$

The last step is to rank these models according to their likelihood values (Eq. (A.8)), so that the ones with a smaller negative log-likelihood (NLL) receive greater weight in the final solution. Specifically, we define the globally optimal result as a rank-weighted combination of all the M candidates;

$$\hat{\mathcal{S}} = \sum_{m=1}^{M} \omega_m \, \mathcal{S}^{(m,\star)}, \tag{A.10}$$

which includes the final reported parameter estimates;

$$\widehat{\theta} = \sum_{m=1}^{M} \omega_m \widehat{\theta}^{(m,\star)}$$

— where each $\widehat{\theta}^{(m,\star)}$ combines the fixed variance vector $\theta_V^{(m,\star)}$ with the estimated parameter vector $\widehat{\theta}_p^{(m,\star)}$ — and the final recovered weight series:

$$\widehat{w}_t = \sum_{m=1}^{M} \omega_m \widehat{w}_t^{(m,\star)}.$$

The rank-weights ω^m are determined by the inverse ranks of the solutions, akin to the method described in Aiolfi and Timmermann (2006). Precisely, let r_m denote the rank of solution m, with $r_m = 1$ corresponding to the lowest NLL (best) and $r_m = M$ to the highest (worst). Then, the weights are defined as:

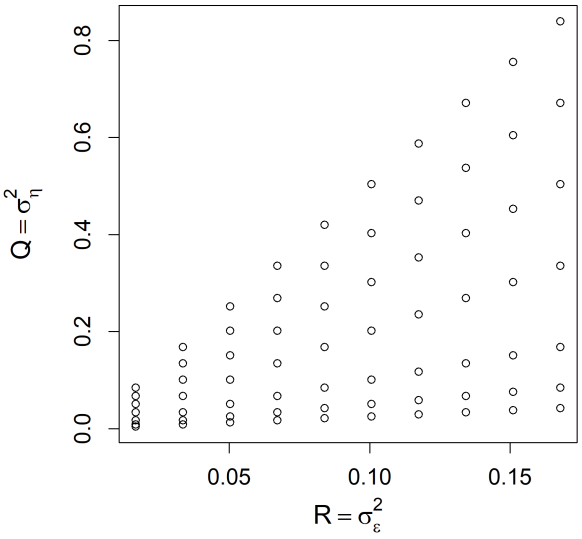
$$\omega_m = \frac{M - r_m + 1}{\mathcal{M}}. \tag{A.11}$$

, where $\mathcal{M} = \frac{M(M+1)}{2}$.

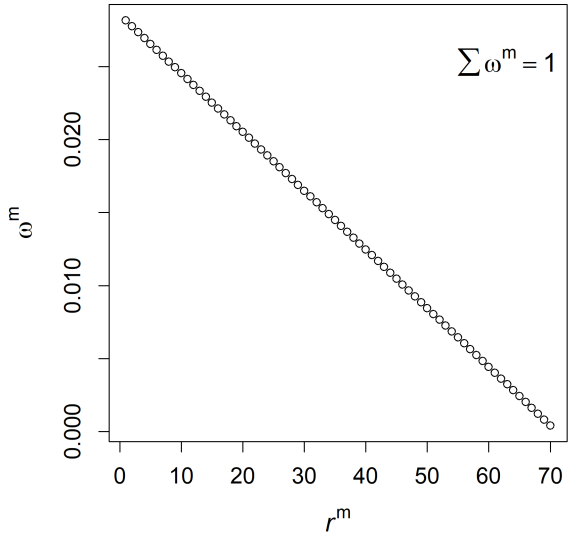
In Figure A.1 we visualize the optimization grid (Panel A) and the rank-weighting (Panel B) from Eq. (A.11) for our case of $M = 70$, to show that the weights — which sum to 1 — are effectively linear in ranks. The idea behind combining multiple solutions is to acknowledge model uncertainty and to benefit from any potential "diversification gains" across models (Timmermann, 2006). Before computing the ranks and weights, we discard solutions for which the scaling factor did not converge or where the parameter estimates did move relative to their starting values.

Figure A.1: Kalman Filter Optimization, $M = 70$

This figure provides an illustration for two key elements in our Kalman filter optimization routine. Panel A presents the signal-to-noise search space that we consider when optimizing the baseline version of the model, which contains $M = 70$ possible ratios in total. Panel B is a graphical representation of the rank-weighting formula from Eq. (A.11), where the sum of the weights is equal to 1.



(A) Signal-to-Noise Grid



(B) Rank Weights

A.3 Confidence Intervals and Hypothesis Testing: Bootstrapping Approach

To assess the finite-sample uncertainty of the estimated parameters obtained from the rank-weighted Kalman filter solution as described in Appendix A.2.3, we use a residual bootstrapping technique. This approach follows the stationary block bootstrap of Politis and Romano (1994), adapted to a state-space setting with latent components and potentially (serially) correlated shocks. Using our bootstrapping strategy, we carry out two types of tests: one where we simulate measurements under the alternative (H_a), and one in which we simulate under the null (H_0). The former allows us to quantify the uncertainty around the Kalman filter estimates, and the latter tells us whether the estimates are significantly different from their assumed null-values. Our first step in implementing the residual bootstrap is to take the estimates coming from the final rank-weighted Kalman-filtering solution (Eq. A.10);

$$\hat{\mathcal{S}} = \{\hat{w}_t, \hat{\theta}_p\}, \quad \text{with} \quad \hat{\theta}_p = \left[\hat{\beta}, \hat{w}_0, \hat{\gamma}, \hat{\phi}, \hat{\rho}\right],$$
$$\hat{w}_t = \hat{w}_0 + \hat{\tau}_t + \hat{u}_t,$$

and use these to construct the empirical distribution for the residuals:

$$\tilde{\varepsilon}_t = e_t, \tag{A.12}$$
$$\tilde{\zeta}_t = \hat{\tau}_t - \hat{\tau}_{t-1} - \hat{\gamma}, \tag{A.13}$$
$$\tilde{\eta}_t = \hat{u}_t - \hat{\phi}\hat{u}_{t-1}, \tag{A.14}$$
$$\tilde{\xi}_t = \hat{\mu}_t - \hat{\rho}\hat{\mu}_{t-1}, \tag{A.15}$$

where $\hat{\tau}_t$, $\hat{u}_t$, are the state-estimates from the trend and cycle components of $\hat{w}_t$, respectively, $\hat{\mu}_t$ is the recovered process for discount rates, and e_t is the innovation defined in Eq. (A.3).

We then perform the bootstrap by sampling, with replacement, 10 blocks[4] of the time-series from this empirical distribution of the residuals. We repeat this for $B = 500$ rounds, and in each of the rounds we simulate different measurements from our system:

[4] A common rule of thumb for the block size in a time-series bootstrap is to use $T^{\frac{1}{3}}$. For our $T = 732$ months, this comes reasonably close to a value of 10 blocks. For an in depth discussion of optimal block sizes see e.g., Hall et al. (1995).

$$
\begin{aligned}
\tau_t^{(b)} &= \tau_{t-1}^{(b)} + \gamma + \tilde{\zeta}_t^{(b)}, \\
u_t^{(b)} &= \phi\, u_{t-1}^{(b)} + \tilde{\eta}_t^{(b)}, \\
\mu_t^{(b)} &= \rho\, \mu_{t-1}^{(b)} + \tilde{\xi}_t^{(b)}, \\
w_t^{(b)} &= w_0 + \tau_t^{(b)} + u_t^{(b)}, \qquad \text{(A.16)} \\
dp_t^{(b)} &= \beta \left[w_t^{(b)} EXP_t^{RI} + (1 - w_t^{(b)}) EXP_t^{PRO} \right] + \mu_t^{(b)} + \tilde{\varepsilon}_t^{(b)}, \qquad \text{(A.17)}
\end{aligned}
$$

where — as before — we initialize $\tau_0 = u_0 = \mu_0 = 0$.

For each bootstrap sample, the entire KF procedure is re-estimated over the simulated measurement $dp_t^{(b)}$ using the optimization routine described in Section A.2, producing a new set of rank-weighted estimates:

$$\{\hat{w}_t^{(b)}, \hat{\theta}_p^{(b)}\}.$$

By bootstrapping over the complete optimization process, we quantify the dispersion of the entire estimation routine, including the final step of rank-weighting the parameter estimates. Additionally, given that each b reaches a rank-weighted solution for the $(\sigma_\varepsilon^2, \sigma_\eta^2)$ signal-to-noise pairs, we can capture their variability by computing standard errors across bootstrap samples. Similarly, using Eq. (A.16), this allows us to compute confidence intervals around the estimated weights themselves.

The bootstrapping procedure under H_0 is virtually identical to the one for H_a. The only difference is that in the former case we set $\theta_p = \theta_p^0 = [\beta^0, 1, 0, 0, 0]$[5] to simulate the measurements $dp_t^{(b)}$, instead of using the rank-weighted estimates coming from the optimized Kalman filter. Under the null hypothesis, the bootstrap procedure generates the sampling distribution of our estimators implied by the model restrictions. This allows us to compute empirical p-values as the proportion of bootstrap draws whose deviation from the null value is at least as extreme as that observed in the actual estimate.

[5]To test the null, we cannot set $\beta = 0$ as for the other parameters in the model, since it would lead to identification problems in our measurement equation. Setting $\beta = 0$ would imply that no variation in the dp-ratio comes from w_t, which renders its parameters unidentifyable. Therefore, when bootstrapping under H_0, we fix it at the initialization value coming from the Flow-of-Funds data as described in Section A.2.1. The assumption that $w_0 = 1$ under the null hypothesis is reflecting the idea that at the beginning of the sample only household expectations matter for asset prices, in the same spirit as the horizontal dashed line from Figure 2.

B Households' Stock Market Direct Ownership: Estimates from Administrative Data

To calculate retail investors' direct share of equity market value, we combine data from several sources, as outlined below. First, we use data from Table 1 French (2008), that offers a detailed accounting of stocks' ownership for the sample period 1980 to 2007. For all remaining periods, the main data source is the Federal Reserve Flow of Funds (FoF), as well as a host of supplementary material, as explained below. The description that follows is based on Tables available from the FoF as of the time of first data collection in 2018. For the period after 2007, we use data from the Flow of Funds (FoF) tables B.101e, B.101H, and L.223, as well as data from the Investment Company Institute (ICI) Factbook. FoF Table B.101H provides the total dollar value of equity holdings (direct and indirect) by Households in the US since 1987. We calculate the total share of Households' equity holdings by dividing such dollar amount by the total value of corporate equities from table L.223. Finally, to obtain Households' direct equity share, we subtract Households' indirect share of equities, which we calculate as mutual funds' share of the equity market from table L.223, times the ICI individuals' share of equity mutual funds.

For the period prior to 1980, data on Households' holdings of equity is not available directly, since the FoF only provides overall holdings of equity by the "Households and Non-Profit Organizations." We therefore have to first remove the impact of non-profit organizations. To do so, we complement the aforementioned data with estimates on the size of non-profit sector, as represented by the number of entities registered as non-profit organizations in the US according to the IRS. Such estimates are reported by the National Association of Non-Profit Organizations and Executives (NANOE) here and Arnsberger et al. (2008). We interpolate linearly such estimates to obtain a quarterly time-series of the number of non-profit organizations between 1960 and 1980. We then calculate non-profit organizations share of equity in a generic quarter q prior to 1980, as French (2008) 1980 non-profit share times the ratio of quarter-q size of the non-profit sector to its size in 1980. Then we remove the "Households and Non-Profit" (HNP) share (direct and indirect) of equities, which is calculated as the ratio of the dollar value of holdings by HNP in table B.101e, to the total value of equities in table L.223. Finally we calculate households' direct share of equity by removing the individuals' share of equity mutual funds holdings. This last step is the same as that outlined above for the post 2007 period.

It is worth mentioning two potential pitfalls with the procedure outlined above. First, when calculating retail investors' share of the equity market, we do not consider the dis-

tinction between domestic and foreign equities. This is essentially due to data limitations, since most of the Flow of Funds data on households and non-profit organizations does not make this distinction. On the other hand, for the majority of our sample period, ownership of domestic-only and total (i.e.,domestic plus foreign) equity are essentially the same. It is only after 2000 that the difference between the two has increased. Given our use of French (2008) data between 2000 and 2007, any mistake from this approximation is likely to be confined to the decade 2007 - 2017. The second limitation of the procedure outlined above stems from the fact that the Flow of Funds data on "Households and Non-Profit Organizations" (HNP) is obtained as a residual from the FoF allocation of assets to modeled economic entities. As such, any such entity whose account is not kept separately by FoF (e.g., hedge funds) falls into the HNP sector. On the other hand, when comparing French (2008) implied total share of equity market by the retail investors in 1980 (56%) with the estimate obtained using our procedure and the Flow of Funds account data (60%), we find the discrepancy fairly small.

C The Determinants of Long-Run Variation in Retail Investor Influence: Event Classification assisted by an LLM

Section 5.2 presents an analysis on the long-run drivers of Households' influence on stocks. This analysis is based on a classification of events that is aided by a Large-Language Model. The purpose of this Appendix Section is to provide further information on this procedure.

C.1 Prompts

The classification we conduct entails prompting the OpenAI 4o-mini reasoning model using the OpenAI API. The model is provided with information about an event, and asked to classify whether the event is expected to increase of decrease the influence of Households on asset prices in the long-run. The model is also asked to provide the economic rationale a financial economist would provide for the classification, and a degree of confidence in the classification. The full prompt is reported below, and it is organized in a *System* component, and a *User* component. Roughly speaking, the System Prompt describes the task, particularly with respect of the meaning of Households' influence, while the User Prompt informs on the desired output information and formatting.

System Prompt

```
SYSTEM_PROMPT = """
You are an expert financial economist. Classify ONE US financial-market event
    in isolation.

Do not compare the event to other events, do not rank events, and do not use
    relative language (e.g., more than, less than, compared to).

Definition (apply literally):
Retail investor influence is how much US stock prices and trading reflect
households beliefs and preferences rather than professionals beliefs/
    preferences and constraints.
Households may trade directly or participate via delegation.

Retail influence DECREASES if in the long-run the event is expected to:
- increase delegation of households investment decisions to intermediaries, OR
```

```
- increase professionals/institutions freedom to invest independently of
    households (lower household/regulatory accountability).

Retail influence INCREASES if in the long-run the event is expected to:
- increase scrutiny/accountability of professionals/institutions by households
    or regulators, OR
- lower barriers/costs/info frictions for households to participate directly in
     US stocks, PROVIDED participation is not primarily via increased delegation
    .

Choose AMBIGUOUS if multiple mechanisms point in opposite directions and
    neither clearly dominates in the long-run.

More participation in the US stock market $\neq$ automatically more influence:
    decide whether households beliefs/preferences become more price-relevant vs
    the preferences/beliefs of intermediaries.

Decision rule for long-run classification:
Ask: In the steady-state after the event and implementation/adoption,
do households beliefs and preferences affect prices more directly,
or are prices more determined by professionals views and their constraints?

Output MUST be a single JSON object only. No extra text. If evidence is mixed,
    choose "Ambiguous" and reduce confidence.
Keep rationales 50 words each; revise until within limit.
"""
```

User Prompt

```
USER_PROMPT = """
USER INSTRUCTIONS:

Event:
Name: {name}
Date: {date}
Description: {description}



Classify the following single event in isolation.

Tasks:
1) event_subject: Identify which group is the direct subject in the event, with
     respect to the ability to trade/participate in the US stock market and
    contribute to price determination:
   - "Retail Investors/Households", "Professional Investors/Institutional
    Investors", or "Ambiguous".
2) effect_on_retail_influence_long_run: Classify the long-run (5 to 10 years
    after the event), persistent directional effect of the event
on retail investor influence after adoption/implementation, ignoring short-term
     reactions.
3) rationale_effect_on_retail_influence_long_run:Provide an economic rationale
    that explicitly references the key mechanism(s) from the definition (No
    boilerplate explanation):
   - increases/decreases delegation, increases/decreases institutional freedom,
     increases/decreases institutions' accountability, increases/decreases
    Households' direct access to US stocks.
4) confidence_effect_on_retail_influence_long_run: Provide confidence scores
    for your judgment on the effect of the overall effect of the event on retail
     investors' influence: Very High/High/Medium/Low/Very Low
5) rationale_event_subject: Provide an economic rationale for why the selected
    market participant is the one directly subject to the event (No boilerplate
    explanation)
 Note: event_subject does not determine effect_on_retail_influence_long_run ;
    effect_on_retail_influence can take any value irrespective of what event
    subject you identify.
```

```
Return valid JSON with exactly these fields:
- Name: {name}
- Date: {date}
- Description: {description}
- event_subject: "Retail Investors/Households" | "Professional Investors/
    Institutional Investors" | "Ambiguous"
- effect_on_retail_influence_long_run: "Increase" | "Decrease" | "Ambiguous"
- rationale_effect_on_retail_influence_long_run: 50 words maximum
- confidence_effect_on_retail_influence_long_run: Very High/High/Medium/Low/
    Very Low
- rationale_event_subject: 50 words maximum

All rationale fields must be plain text strings with no line breaks.
"""
```

C.2 LLM Events

In Table C.1 we present the list of events used in the analysis of Section 5.2, as well as the LLM classification and the rationale for the classification functionality.

Table C.1. Summary of LLM Events

Label	Date	Description	Cat.	HH Influence	Rationale	Conf.
SEC Acts Amendments	Aug 1964	Extended SEC disclosure & reporting to many OTC firms- tightened broker-dealer regulation	IREG	Increase	Mandatory disclosure and reporting for OTC firms and tightened broker-dealer regulation increases institutional accountability to regulators, reduces professionals' trading autonomy, and lowers information frictions for direct household participation, thereby increasing the weight of household preferences in price setting.	High
SIPA	Dec 1970	Securities Investor Protection Act creates SIPC to insure brokerage customer assets and bolster investor confidence after broker failures	IREG	Increase	By insuring customer assets, SIPA lowers households' counterparty risk and costs, improving direct market participation and reducing institutions' relative price influence via lower frictions.	High
MM Funds	Jan 1971	Low-risk mutual fund-like cash product. Introduction of money market mutual funds as open-end mutual funds investing in short-term debt instruments, designed for cash management and liquidity (e.g., early US funds beginning in 1971)	TCMM	Decrease	MM funds increased delegation of households' cash holdings to fund managers, giving professionals discretion over asset selection in short-term debt and reducing households' direct engagement with markets. This enduring delegation lowers the direct price impact of households' preferences on US stock valuations.	High
NASDAQ	Feb 1971	First electronic stock market. Launch of NASDAQ as an electronic quotation system and stock market operated by the National Association of Securities Dealers (NASD), commencing operations on February 8, 1971	TCMM	Increase	The electronic quotation system reduced information frictions and trading costs, enhancing households' direct access to stock prices and trading, increasing weight of their preferences in price determination.	High
Cboe	Apr 1973	Cboe begins standardized listed equity options trading, expanding hedging/leverage instruments linked to stocks	TCMM	Decrease	Standardized options expanded institutions' hedging and leverage capacity, increasing professionals' freedom to tailor risk and decouple portfolios from household constraints, reducing the direct price impact of retail beliefs.	High
DTC	May 1973	Depository Trust Company begins centralized book-entry settlement, reducing back-office frictions and settlement risk	TCMM	Decrease	Centralized book-entry settlement reduces back-office frictions for intermediaries, boosting professional trading capacity and autonomy, thereby increasing institutional freedom and reducing retail investors' direct price impact.	High
Phone Trading	Jan 1974	Toll-free trading service. Introduction of brokerage services that enabled customers to place securities orders by telephone (including toll-free access), complementing in-person and mail-based brokerage channels	TCMM	Increase	Phone trading increased households' direct access to US stocks by lowering transaction costs and info frictions, reducing reliance on intermediaries and increasing households' price-relevant participation.	High

ERISA / IRA	Sep 1974	Pension and IRA accounts with tax deferral. Enactment of ERISA (effective September 2, 1974), establishing federal standards for private-sector retirement plans and fiduciary responsibilities; accompanied by creation and expansion of tax-advantaged individual retirement.	IREG	Decrease	The expansion of tax-advantaged IRAs funneled household savings into managed retirement vehicles, increasing delegation to intermediaries and reducing households' direct impact on price formation.	High
Index Funds	May 1975	Launch of index fund model. Introduction of index-tracking mutual funds for individual investors, including Vanguard's First Index Investment Trust (later the Vanguard 500 Index Fund) launched in 1976	TCMM	Decrease	Index funds channel household capital through professional managers, increasing delegation and replacing direct retail stock selection with passive benchmark tracking, reducing the weight of individual investors' beliefs in price formation.	High
May Day	May 1975	SEC elimination of fixed-rate brokerage commissions on US exchanges effective May 1, 1975, requiring commissions to be negotiated between brokers and customers (the end of fixed commission schedules). This allows for competition among brokers in rates offered to customers.	TCMM	Increase	Elimination of fixed commissions lowered transaction costs, increasing households' direct access to US stocks and reducing delegation, so retail beliefs carry more weight in prices.	High
SEC NMS	May 1975	Securities Acts Amendments mandate National Market System and national clearance & settlement (enacted June 4, 1975)	IREG	Increase	SEC NMS unified national quotation and settlement systems reduced execution costs and information frictions, lowering barriers for households to place orders and see prices directly, boosting retail direct access and thus increasing household beliefs' price relevance.	High
NSCC	Mar 1976	National Securities Clearing Corporation is formed to provide centralized clearing and netting for US securities trades	TCMM	Decrease	Centralized netting reduces settlement costs and risks for intermediaries, expanding institutions' trading capacity and autonomy. This increased freedom for professionals to execute large volumes lowers households' relative price impact, diminishing retail investors' direct influence on stock prices.	High
401(k)	Nov 1978	Employer-based tax-deferred retirement plan. Creation of Internal Revenue Code Section 401(k) in the Revenue Act of 1978, enabling salary-deferral contributions to qualified employer-sponsored retirement plans; early adoption and implementation followed	IREG	Decrease	401(k) structures channel household savings into professionally managed funds, increasing delegation of investment decisions to intermediaries and reducing direct household price impact.	High
MF Ads	Aug 1979	Simplified mutual fund advertising. SEC adoption of Securities Act Rule 482 (1979), permitting mutual funds to advertise selected information derived from the statutory prospectus, subject to specified disclosure and liability provisions	IREG	Decrease	Rule 482 enabled funds to market products directly to households, boosting household flows into pooled vehicles and raising professional managers' discretion, thereby increasing delegation of investment decisions and reducing direct household influence on stock prices.	High

MF SEC 12b-1	Oct 1980	SEC adopts Rule 12b-1 allowing mutual funds to use assets to pay for distribution/marketing, altering fund industry incentives and scale	IREG	Decrease	Rule 12b-1 funded marketing via mutual fund assets expands intermediated distribution, boosting household delegation to funds and reducing households' direct price influence through increased reliance on professionals.	High
401(k) Clarified	Nov 1981	Contribution rules clarified. IRS issuance of proposed regulations in November 1981 clarifying the operation of 401(k) salary-deferral plans (including permissible deferrals and related requirements), facilitating broader employer adoption	IREG	Increase	Clarification lowered frictions for employees to invest retirement savings in equity, boosting direct household access to US stocks without primarily increasing delegation, raising the relevance of household preferences in price formation.	High
S&P500 Futures	Apr 1982	CME launches S&P 500 index futures (April 21, 1982). Introduction of S&P 500 stock index futures trading by the Chicago Mercantile Exchange in 1982, providing standardized equity index derivatives for hedging and speculation	TCMM	Decrease	Futures enable professionals to hedge equity exposure and implement macro views without moving stocks, increasing institutional independence and reducing households' price impact.	High
MMDAs	Dec 1982	Money Market Deposit Accounts. Authorization of money market deposit accounts (MMDAs) under the Garn–St Germain Depository Institutions Act of 1982, creating an interest-bearing bank deposit account product for households.	IREG	Ambiguous	MMDAs provide households an interest-bearing deposit alternative without altering direct access or delegation to stock markets, leaving both retail direct access and professional influence largely unchanged.	High
NYSE SuperDOT	Jan 1984	NYSE introduces SuperDOT electronic order routing, enabling faster automated order submission and facilitating program trading	TCMM	Decrease	SuperDOT enabled institutions to execute program trades faster and in greater volume, increasing professionals' unconstrained trading capacity, thereby raising their share of order flow and price impact and reducing relative influence of households' direct orders.	High
SIA v Fed	Apr 1984	Supreme Court case Securities Industry Association v. Board of Governors (decided June 28, 1984) addressing the scope of activities permitted for bank affiliates under federal banking and securities laws. Court allows banks to sell mutual funds.	IREG	Decrease	Bank affiliates can sell mutual funds, boosting household investing through intermediaries increases delegation of decisions to professionals, reducing direct household price impact.	High
Schwab Software	Jun 1984	Trading software for clients. Introduction of personal-computer-based brokerage tools and software that enabled investors to access quotes and place or manage trades electronically through a retail brokerage platform	TCMM	Increase	The software lowered barriers and information frictions for households to trade directly in US stocks, enhancing their ability to place orders without intermediaries and thereby increasing retail investors' direct influence on price formation.	Very High
Banks 5% Revenue	Dec 1986	Regulatory change/interpretation expanding the allowable share of a bank's revenue from certain securities-related activities for banking organizations, subject to supervisory constraints.	IREG	Decrease	Regulatory expansion grants banks greater securities-trading authority, boosting institutional freedom to trade independently of households and reducing households' direct price impact.	High

Black Monday	Oct 1987	Stock market crash	TCMM	Decrease	Retail confidence collapsed, boosting delegation of household assets to intermediaries; long-run portfolio allocations shifted towards managed accounts, increasing professionals' decision-making relative to direct household trading.	Medium
Performance Ads	Feb 1988	Standardized fund performance ads. Development and enforcement of standardized requirements for presenting investment performance in advertising and marketing materials, including disclosures and calculation conventions for returns	IREG	Decrease	Standardized performance ads channel households into mutual funds, boosting delegation of investment decisions to fund managers. Increased fund flows amplify professionals' trading power and diminish households' direct price impact in US stocks.	High
Basel I	Jul 1988	Capital requirements for banks. Publication of the 1988 Basel Capital Accord establishing minimum risk-based capital standards for internationally active banks, later implemented by national regulators	IREG	Increase	Basel I imposes risk-based capital constraints on banks, increasing regulatory scrutiny and reducing institutions' freedom to invest independently, thereby elevating the relative direct influence of households' preferences on price formation.	High
MWCB	Oct 1988	Market-wide circuit breakers (post-1987 crash) are adopted to pause trading after large index moves, constraining program trading feedback loops	IREG	Increase	Circuit breakers constrain institutional program trading by pausing market moves, reducing professionals' freedom to trade independently of households and thereby raising the relative price impact of direct retail trades.	High
Banks 10% Revenue	Jan 1989	Revenue cap increased for bank securities. Regulatory change/interpretation expanding permitted securities-related activities for banking organizations subject to revenue limits and supervisory conditions (including higher allowable revenue shares)	IREG	Decrease	Expanding banks' securities revenue cap boosts institutional trading freedom, raising professional activity and autonomy. This shifts price determination toward institutions and away from households, reducing the long-run weight of retail beliefs in US stock prices.	High
CNBC	Apr 1989	CNBC launches as a dedicated business news channel, expanding real-time market information and investor attention among households	SFIN	Increase	The addition of real-time market news lowers households' information frictions and barriers, increasing direct access to stock data and choices, thus boosting households' capacity to trade and affect prices without reliance on intermediaries.	High
SEC 144a	Apr 1990	SEC adopts Rule 144A to facilitate resale of restricted securities to Qualified Institutional Buyers, deepening institutional private markets	IREG	Decrease	Rule 144A increases professionals' freedom to invest independently by expanding institutional private markets, reducing relative price impact of household trading.	High
SPDR ETF	Jan 1993	First major US ETF (SPDR S&P 500) launches, enabling low-cost intraday diversified exposure and new arbitrage/creation-redemption trading	TCMM	Increase	By reducing trading costs and frictions and enabling intraday diversified exposure without intermediated delegation, ETFs enhance households' direct access to US stocks, boosting weight of household beliefs in price formation.	High
EDGAR E-filings	Apr 1993	SEC begins mandating electronic filings via EDGAR, sharply reducing disclosure access costs and speeding information diffusion	IREG	Increase	EDGAR sharply reduces information costs for households, enabling direct interpretation and trading on firm disclosures rather than via intermediaries, expanding direct retail access and price impact.	High

Motley Fool	Jul 1993	The Motley Fool launches investing media/advice for retail audiences, lowering information/search costs and amplifying retail sentiment	SFIN	Increase	The Motley Fool's advice platform reduces households' information and search costs, boosting direct retail trading and sentiment transmission into equilibrium prices without altering delegation to professionals.	High
Mellon Letter	May 1994	OCC letter clarifying incidental power. Regulatory or interpretive guidance letter affecting permissible activities or product offerings by a financial institution (issued in the context of bank-affiliate securities or investment activities). The OCC recognized that national banks have incidental powers necessary to carry on the business of banking, including activities that protect a lender's interest in its loans, such as insurance products or managing risks.	IREG	Decrease	The OCC letter broadened national banks' incidental securities powers, increasing intermediaries' freedom to create and trade financial products independently of households, raising professionals' portfolio autonomy and thus reducing the relative price impact of direct retail beliefs or preferences.	High
NBank v VALIC	Jan 1995	Supreme Court case validates bank mutual fund sales. Judicial decision addressing the permissibility of banks selling annuity or insurance-related investment products under federal banking law and the scope of related restrictions	IREG	Decrease	The ruling expands banks' ability to distribute mutual funds, increasing household delegation to bank intermediaries and boosting professionals' freedom to invest independently of direct retail trading, reducing households' direct price impact.	High
Online Trading	Jan 1996	Internet-based trading launched. Adoption of internet-based brokerage platforms enabling customers to view account information and submit securities orders electronically via online interfaces	TCMM	Increase	Internet-based platforms lowered transaction costs and information frictions, enabling households to trade directly rather than delegate, thus increasing their price impact over time.	High
NSMIA	Oct 1996	National Securities Markets Improvement Act preempts many state securities regulations and streamlines rules for mutual funds/advisers, enabling scale	IREG	Decrease	NSMIA streamlined advisor and fund registration, enabling mutual fund complexes to scale nationally. It increases households' delegation and professional freedom by reducing state oversight, shifting price setting toward institutions.	High
Banks 25% Revenue	Dec 1996	Revenue cap increased to 25%. Regulatory change/interpretation further expanding the allowable share of revenue from certain securities-related activities for banking organizations, subject to supervisory constraints	IREG	Decrease	Expansion increases institutional freedom to trade independently, reducing households' direct price impact by shifting trading volume toward professional intermediaries.	High
SEC OHR	Jan 1997	SEC Order Handling Rules require display of customer limit orders and integrate ECN quotes, improving price competition and transparency	IREG	Increase	Mandatory display of customer limit orders and ECN quotes reduced households' information frictions, lowering barriers to direct trading and making retail preferences more price-relevant.	High
Yahoo Finance	Jan 1997	Yahoo Finance launches, giving households free real-time quotes, news, and portfolio tools at scale	SFIN	Increase	Yahoo Finance reduced information frictions by offering free real-time quotes and portfolio tools, lowering households' costs and barriers to direct stock analysis and trading, thus increasing the relevance of household preferences in price formation.	High

Tick Size 1/16	Jun 1997	Reduction of minimum price increment. Reduction of minimum tick size on US equity markets to one-sixteenth of a dollar for many stocks, changing quoting and execution increments prior to full decimal pricing	TCMM	Increase	The 1/16 tick size reduces transaction costs, lowering barriers for households to trade stocks directly, increasing direct access and price relevance of retail orders.	High
E-Mini S&P500	Sep 1997	CME introduces E-mini S&P 500 futures products, lowering contract size and margin needs and widening access to index trading for smaller traders	TCMM	Increase	E-mini S&P futures lowers contract size and margin, reducing barriers and information frictions for households to trade index futures directly, enhancing their ability to express beliefs. This expanded direct market access increases the price relevance of retail preferences in the long run.	High
SEC Reg ATS	Dec 1998	SEC adopts Regulation ATS creating a regulatory framework for alternative trading systems (ECNs/dark pools), reshaping fragmentation and institutional execution	IREG	Decrease	Reg ATS expanded venues (ECNs/dark pools) for institutional execution, increasing professional freedom to trade away from public markets and reducing direct price impact of household orders.	High
GLB Act	Nov 1999	Banks allowed to acquire non-banks. Enactment of the Gramm–Leach–Bliley Act (signed November 12, 1999), removing key Glass–Steagall barriers and permitting affiliations among banking, securities, and insurance firms	IREG	Decrease	The Act expanded banks' securities operations, fostering consolidation that encourages retail clients to delegate account management. It increased professional investors' freedom to trade across sectors, reducing the long-run price impact of households' direct stock preferences.	High
FHC	Mar 2000	Banks convert to financial holding companies. Introduction of the financial holding company (FHC) framework under Gramm–Leach–Bliley, allowing eligible bank holding companies to engage in a broader set of financial activities subject to regulatory conditions. Several banks convert to FHC immediately after.	IREG	Decrease	The FHC framework expands banks' freedom to invest across securities, insurance, and merchant banking, increasing professional institutions' independent trading and boosting households' delegation to intermediaries, thereby reducing direct household price influence.	High
SEC Reg FD	Oct 2000	Regulation Fair Disclosure restricts selective disclosure to analysts, reducing information advantages of institutions and broadening public info access	IREG	Increase	Reg FD reduces institutions' private information advantages by mandating broad public disclosures, lowering households' information frictions and increasing their direct price impact. No change in delegation; professionals' informational freedom declines.	High
SEC 605/606	Nov 2000	SEC adopts execution quality (Rule 605) and order-routing (Rule 606) disclosures, increasing transparency about broker execution and payment-for-order-flow incentives	IREG	Increase	Disclosure of execution quality and payment-for-order-flow increases regulatory and retail scrutiny of broker routing decisions, raising accountability of intermediaries and aligning order executions with household preferences, thereby amplifying the direct influence of retail investors on price determination.	High

CFMA	Dec 2000	Commodity Futures Modernization Act of 2000,The act explicitly exempted most over-the-counter derivatives—specifically swaps—from oversight by the Commodity Futures Trading Commission (CFTC) and the Securities and Exchange Commission (SEC). This created a "hands-off" approach to derivatives trading, particularly among "eligible contract participants" (e.g., banks, hedge funds).	IREG	Decrease	The CFMA increases institutional freedom by removing CFTC/SEC oversight of OTC derivatives, expanding professional trading with lower regulatory accountability and leaving households confined to regulated instruments, thus diminishing the direct price relevance of retail investors' beliefs.	High
Decimalization	Apr 2001	Prices quoted in cents. Conversion of US equity markets from fractional to decimal price quotations, with exchanges completing the transition to penny pricing by April 9, 2001.This results in a reduction in tick size	TCMM	Decrease	Decimalization reduced tick sizes, benefiting high-frequency and institutional liquidity provision, increasing their trading freedom and sophistication. Retail access costs changed minimally, shifting price formation weight toward professional strategies and away from household order flow, thereby lowering retail investor influence.	Medium
SOX	Jul 2002	Corporate accountability regulations. Sarbanes–Oxley Act of 2002, strengthening public-company reporting, internal control, and audit requirements following major corporate accounting scandals	IREG	Increase	Enhanced corporate disclosures under SOX reduce information frictions and lower access costs for households to evaluate stocks directly, boosting the price relevance of retail beliefs without increasing delegation.	High
MF Timing Scandal	Sep 2003	Mutual fund late-trading/market-timing scandal exposed- subsequent rules and settlements curb abusive timing	IREG	Increase	Post-scandal reforms imposed tighter rules and enforcement on mutual fund trading, increasing institutional scrutiny and accountability to shareholders, which boosts the weight of household oversight and raises retail investors' price relevance through enhanced monitoring of professional asset managers.	High
MF Compliance	Feb 2004	SEC adopts fund/adviser compliance program rules (incl. CCO requirement) after late-1990s/early-2000s scandals, raising governance and reducing agency problems	IREG	Increase	Mandating compliance programs and Chief Compliance Officers increases institutional accountability and oversight, aligning fund management more closely with household interests and enhancing direct retail investor influence on prices through regulators' enforcement of end-investors' preferences.	High
Seeking Alpha	Jun 2004	Investment info and analysis platform. Launch and growth of Seeking Alpha (founded mid-2000s) as an online platform publishing crowd-sourced financial commentary, stock analysis, and market news accessible to investors	SFIN	Increase	The platform reduces information frictions and lowers barriers for households to access analysis, boosting their direct engagement and the weight of their beliefs in price formation.	High
SEC Reg SHO	Jan 2005	Regulation SHO imposes locate/close-out requirements and short-sale marking, curbing fails-to-deliver and altering short-selling economics	IREG	Increase	Reg SHO imposes locate, mark and close-out mandates on short-sellers, increasing institutions' accountability via heightened regulatory oversight and constraining professional trading, thereby boosting households' relative price influence.	High

SEC Reg NMS	Jun 2005	Regulation NMS (Order Protection, Access, and related rules) reorganizes intermarket routing and quoting, accelerating fragmentation and high-speed competition	IREG	Decrease	Reg NMS increased professionals' freedom to trade across fragmented venues, not lowering info frictions for households or boosting direct access, diminishing household price impact.	High
NYSE/Arca Merger	Mar 2006	NYSE merges with Archipelago (Arca), demutualizing and moving toward an electronic, for-profit exchange model with intensified competition for order flow	TCMM	Decrease	Competition for order flow spurred payment for order flow and internalization, increasing delegation of household trades to brokers and wholesalers, lowering direct household price impact despite electronic trading improvements.	Medium
PPA	Aug 2006	Automatic enrollment into pensions. Pension Protection Act of 2006, revising funding and disclosure rules for defined-benefit plans and changing provisions affecting employer-sponsored retirement plan design and administration. Pension plan providers receive fiduciary relief (lower accountability), and employees are pushed toward default enrollment into 401(k), and incentives to increase contributions to the 401(k) also increase	IREG	Decrease	Automatic enrollment shifts assets into default funds managed by fiduciaries, boosting delegation of household decisions while fiduciary relief reduces institutional accountability, so professional managers' views drive prices more than individual savers' preferences.	High
Repeal of Uptick Rule	Jul 2007	SEC repeal of the long-standing uptick rule (Rule 10a-1), which had restricted short sales to prices above the last different trade. The repeal removed this price test for most US equities, changing the regulatory constraints on short selling.	TCMM	Decrease	The repeal lifted price-test constraints on short selling by professional traders, expanding institutional freedom to trade based on proprietary strategies, thereby reducing the relative price impact of households' views in the steady state.	High
Basel II	Apr 2008	Risk-based capital framework. Publication of the Basel II framework (2004) revising bank capital requirements using a three-pillar structure (minimum capital, supervisory review, and market discipline. More restrictive in scope but less restrictive in its aggregate capital requirements (more flexible) than Basel I, as it was designed to be more risk-sensitive. While Basel II introduced stricter oversight, it allowed banks with advanced, internal risk models to potentially hold less capital for certain types of low-risk loans.	IREG	Decrease	Basel II's risk-based capital rules allow banks using internal models to reduce capital holdings, expanding institutional lending and trading autonomy. This increases professionals' freedom to determine asset portfolios independently of household oversight, reducing households' price impact.	High
StockTwits	Jun 2008	Social finance platform. Launch of StockTwits (founded 2008) as a social media platform for investors, popularizing cashtags (e.g., $AAPL) to organize real-time discussion around securities	SFIN	Increase	StockTwits lowers information frictions by enabling households to share and access real-time security discussions directly, increasing retail investors' direct input into price formation.	High

GS/MS to BHC	Sep 2008	Conversion to bank holding companies. Conversion of Goldman Sachs and Morgan Stanley to bank holding companies in 2008 during the financial crisis, bringing them under Federal Reserve supervision as BHCs	IREG	Decrease	Conversion granted Goldman Sachs and Morgan Stanley access to Fed funding and stable deposits, reducing reliance on market discipline and retail-driven funding. This increases professional investors' freedom to invest independently of households, diminishing households' direct price influence.	High
SEC 201	May 2010	SEC Rule 201 becomes effective (May 10, 2010): circuit-breaker short-sale price test: imposes strict limitations on short selling when a security's price drops by 10% or more from its previous day's closing price.	IREG	Increase	Rule 201 restricts professionals' short-selling freedom in steep price drops, lowering institutional trading freedom and tilting price impact towards households' direct trades.	High
SSCB	Jun 2010	SEC approves single-stock circuit breakers (trading pauses) in response to the May 2010 Flash Crash, limiting extreme short-horizon price dislocations	IREG	Increase	Circuit breakers limit extreme professional trading strategies, reducing institutional freedom to move prices unilaterally, increasing the relative weight of retail orders in price formation.	High
Dodd-Frank	Jul 2010	Financial reform act. Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010, introducing major financial regulatory reforms including enhanced prudential standards and derivatives regulation	IREG	Increase	Dodd-Frank imposes enhanced prudential standards and regulatory oversight on institutions, increasing institutional accountability to regulators, aligning professional behavior closer to households' interests, thus raising the relative influence of retail preferences in price formation.	Medium
SEC Rule 15c3-5	Nov 2010	SEC adoption of Rule 15c3-5 (the Market Access Rule), requiring broker-dealers providing market access to implement risk management controls and supervisory procedures to limit financial, regulatory, and operational risks associated with electronic trading access.	IREG	Decrease	Rule increases brokers' compliance burdens and pre-trade controls, raising barriers for households' direct electronic access and reinforcing delegation to intermediaries, reducing households' direct price impact.	High
Reddit WSB	Jan 2012	Reddit investment forum. Creation and growth of the r/wallstreetbets subreddit (founded January 31, 2012) as an online community focused on high-risk trading discussion among retail participants	SFIN	Increase	The subreddit lowers information frictions and access costs for households, enabling direct trading decisions without delegation, thus amplifying the price impact of retail beliefs in the steady state.	High
SEC 613 CAT	Jul 2012	SEC adopts Rule 613 to create the Consolidated Audit Trail, expanding surveillance and reducing opacity in order/participant behavior across venues	IREG	Increase	Rule 613 expands surveillance of professional trading, increasing institutions' accountability to regulators, which constrains independent professional discretion and elevates household beliefs' price impact.	High
Twitter Cashtags	Jul 2012	Tagged stock mentions on Twitter/X. Adoption and use of cashtags (ticker symbols prefixed with $) on Twitter to index and aggregate discussions about publicly traded companies and financial instruments	SFIN	Increase	Cashtags reduce information frictions by indexing peer-generated stock discussions, increasing households' direct access and price relevance without adding intermediaries, raising retail beliefs' weight in price formation.	High

Basel III	Jan 2013	Strengthened capital and liquidity requirements. Basel III reforms developed after the 2008 crisis, strengthening bank capital, leverage, and liquidity standards through internationally agreed regulatory enhancements	IREG	Increase	Basel III raises banks' capital and liquidity constraints, reducing professional investors' freedom to deploy capital independently. Lower institutional trading power in equities increases relative influence of households' direct beliefs on price formation.	High
LULD	Apr 2013	LULD plan becomes operational, preventing trades outside dynamic price bands and changing short-horizon liquidity provision and volatility dynamics	IREG	Increase	LULD constraints reduce professionals' freedom to trade outside dynamic price bands, limiting institutional strategy scope and raising relative price impact of retail orders.	High
SEC CPR Amendments	Jul 2013	SEC strengthens broker-dealer customer protection/segregation rules, reducing risk of customer asset rehypothecation and broker default spillovers	IREG	Increase	Strengthened segregation rules raise broker accountability to customer interests, making professionals more responsive to retail preferences. This increased institutional accountability amplifies households' price impact, elevating retail influence in the long-run.	High
Robin Hood	Apr 2014	Zero-commission trading app. Launch and expansion of Robinhood as a commission-free trading app (introduced in the 2010s), providing mobile access to trading in stocks and related products for retail customers	TCMM	Increase	Robinhood lowers trading costs and information frictions, increasing households' direct access to US stocks and enabling retail beliefs and preferences to shape prices more directly.	High
Volcker Rule	Apr 2014	Limits proprietary trading by banks. Implementation of the Volcker Rule under Dodd–Frank, restricting proprietary trading and certain relationships with hedge funds and private equity funds for banking entities	IREG	Increase	By restricting banks' proprietary trading, the rule reduces institutions' freedom to trade independently, lowering professional volume and making prices relatively more sensitive to households' orders.	High
SEC Reg SCI	Nov 2014	SEC adopts Regulation SCI requiring exchanges/large ATS to harden systems and report outages, raising fixed costs of sophisticated trading infrastructure	IREG	Increase	Reg SCI imposes higher compliance costs and technical standards on trading venues, reducing professionals' ability to deploy high-frequency and complex strategies, thus limiting institutional trading freedom and enhancing the relative influence of households' orders on prices.	High
DOL Fiduciary Rule	Jun 2016	DOL fiduciary rule effective (June 7, 2016): tightens standards for retirement investment advice	IREG	Increase	The rule increases regulatory accountability of professional advisors to act in households' best interests, raising households' preferences' weight in investment advice and thus in price determination.	High
SEC IEX Approval	Jun 2016	SEC approves IEX as a national securities exchange and clarifies treatment of slight quote delays (speed bump), challenging latency-arbitrage business models	IREG	Ambiguous	The speed bump reduces professionals' arbitrage freedom without lowering household trading frictions or boosting accountability, creating uncertain effects on households' direct influence.	Medium
SEC Liquidity Rules	Oct 2016	SEC liquidity risk management. SEC adoption of liquidity risk management requirements for open-end mutual funds and ETFs, requiring funds to assess and manage liquidity and report related information to regulators	IREG	Increase	These requirements increase scrutiny and accountability of institutional investors by regulators, enhancing retail investors' relative price influence in the long run.	High

Tick Size Pilot	Oct 2016	SEC/FINRA tick-size pilot begins for selected small-cap stocks to test whether wider ticks increase liquidity provision and broker intermediation	IREG	Decrease	Wider ticks boost broker-dealer profits and encourage professional liquidity provision, raising households' reliance on intermediaries (delegation) rather than direct trading. This persistent rise in delegation reduces the direct impact of retail investors' preferences on prices.	High
T+2 Settlement	Sep 2017	US markets move from T+3 to T+2 settlement, reducing counterparty exposure and collateral needs and changing clearing capital economics	TCMM	Decrease	In the long-run, speeding settlement reduces institutions' collateral requirements and counterparty risk, increasing their trading freedom relative to households, thus institutional views more price-determinant.	High
Micro E-minis	May 2019	CME launches Micro E-mini index futures, further lowering contract size and widening access to index trading for small accounts	TCMM	Increase	The launch lowers contract size, reducing barriers for households to trade index futures directly, increasing direct access to US equity exposure and making retail beliefs more price-relevant.	High
SEC Reg BI	Jun 2019	SEC adopts Regulation Best Interest to govern broker recommendations to retail customers, altering conflicts of interest and advice supply. It forces a shift from a transaction-focused model to a client-focused model, requiring brokers to prioritize the customer's interests over their own financial interests.	IREG	Increase	Reg BI increases broker accountability to retail investors by legally obligating advice to prioritize household interests, enhancing households' price impact via improved direct feedback channels, thus increasing scrutiny of professional conduct.	High
$0 Commissions Mainstream	Oct 2019	Major brokerages (e.g., Schwab, Fidelity) cut online US stock/ETF commissions to $0, compressing explicit trading costs for households	TCMM	Increase	Zero commissions lower explicit trading costs and reduce barriers for households to trade directly, enhancing their ability to express preferences in price formation.	High
Stimulus Trading	Mar 2020	CARES Act voted into law and pandemic-era transfers and stimulus checks to households	TCMM	Ambiguous	Stimulus checks gave households additional capital to trade directly, increasing direct access temporarily, but did not change institutional delegation or accountability frameworks, leaving long-term retail influence uncertain.	Medium
GameStop	Jan 2021	Retail-coordinated trading (WSB) triggers extreme short/gamma squeezes (e.g., GameStop), forcing institutions to manage retail flow risk and prompting market-structure scrutiny	SFIN	Increase	Prompted regulatory scrutiny of market structure to address retail-driven volatility, increasing institutional accountability to households and reducing barriers for direct retail participation, thus elevating households' price relevance over professionals in steady state.	Medium

This table shows 83 economic events identified via our API prompt to the OpenAI GPT 4o-mini Large Language Model (LLM), for the period Jan 1963 - Dec 2023. The first column "Label" contains a short name for the event, and the "Date" column represents the timing of the event. In the "Description" column we provide a brief summary for each of the events. The "Cat." column groups events into three categories: Intermediary Regulation (IREG), Trading Cost and Market Microstructure (TCMM), and Social Finance (SFIN). The "HH Influence" column shows the LLMs' prediction as to whether households gain or lose influence on prices as a consequence of being (in)directly impacted by the event under consideration. The "Rationale" column provides a summary as to what motivated the LLM to make the prediction for the influence of households. Finally, the "Conf." column contains the confidence level of the LLM attached to this directional prediction.

D Estimating Retail Investor Influence with Alternative Model Specifications

In the baseline specification of our model, we use the unadjusted monthly log dp-ratio to serve as the LHS signal in the measurement equation that links market valuations to investor expectations:

$$dp_t = \beta \left[w_t EXP_t^{RI} + (1 - w_t) EXP_t^{PRO} \right] + \mu_t + \varepsilon_t.$$

In a second, alternative version of our model, we rely on earlier work by Lettau and Van Nieuwerburgh (2008) to construct a *dp*-ratio that is corrected for structural breaks in the valuation of the market:

$$dp^* = dp_t - d_1 I_1 - d_2 I_2 - d_3 I_3, \tag{D.1}$$

where d_1, d_2, d_3 are the averages of the dp-ratio computed from Jan 1927 - Dec 1954, Jan 1955 - Dec 1994, and Jan 1995 - Dec 2023, respectively. The Is are indicators equal to one for the corresponding period and are zero otherwise.

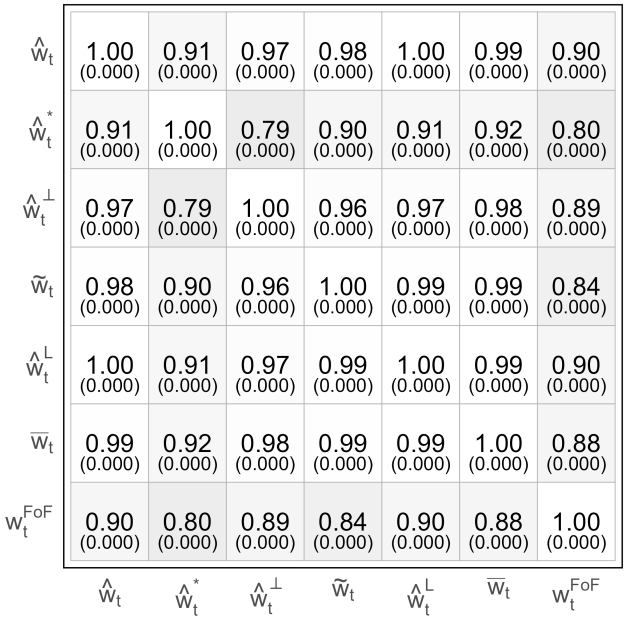
The third variation of our observation model acknowledges the role of risk-aversion and financial uncertainty in driving market valuations, beyond investor beliefs. We account for the risk appetite of consumers and institutions by incorporating the Surplus-Consumption ratio (Cochrane, 2017) and the Intermediary Capital ratio (He et al., 2017), respectively, into our model. As a proxy of macroeconomic risk we use Financial Uncertainty measure developed by Jurado et al. (2015). We control for risk-aversion and financial uncertainty in our measurement equation by orthogonalizing the *dp*-ratio with respect to the three aforementioned variables. Given that the time-series for the Intermediary Capital ratio starts in January 1970, the third version of our KF will use a slightly shorter time-series than the other two that start in 1963.[6] In addition to alternative versions of the measurement equation we consider a modified model for the law-of-motion that describes the trend component of the weights; τ_t in Eq. (3). In this robustness test, we fix in the estimation of the baseline model (using the unadjusted dp-ratio as measurement) the deterministic drift parameter γ to zero instead of estimating it within the KF procedure. We denote the weights coming out of this procedure as $\tilde{w}_t$. Finally, to test sensitivity of the baseline result w.r.t. the grid search optimization, we consider a version of the estimation procedure where we explore 200 possible solutions instead of the 70 from Section A.2.3, by increasing the granularity of the variance ratios grid. In total, we obtain five sets of filtered weights, obtained under different estimation regimes. As a simple benchmark, we create an ensemble of these series by averaging estimates within a month and across models. Figure D.1 shows the raw as well as the detrended correlations between

[6] Prior research shows that not only risk aversion but also subjective cash flow growth expectations drive a substantial part of the variation in the dividend–price ratio. In an alternative specification we account for this by orthogonalizing the dp-ratio w.r.t. the experienced dividend growth variable from Nagel and Xu (2022). The weights we obtain under this approach correlate by 99% to the baseline series (and by 77% once detrended).

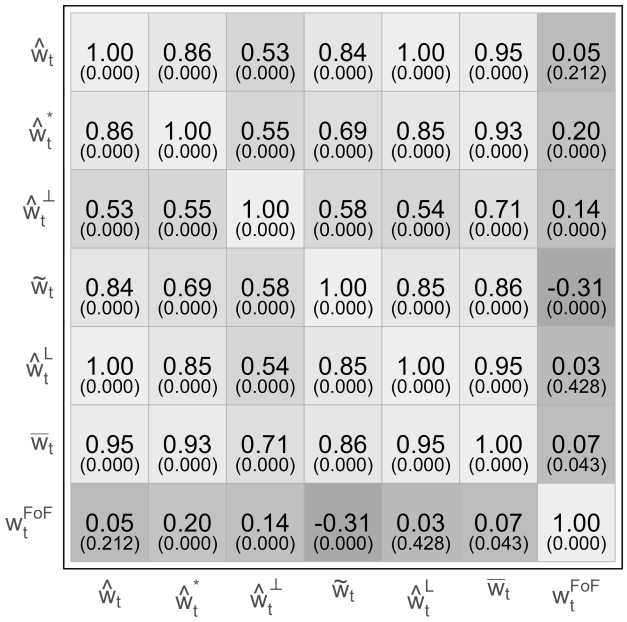
our estimated weights and to the ones based on the Flow-of-Funds data (w_t^{FoF}). Figure 8 plots the time-series path of the estimated series. Finally, Table D.1 shows the parameter estimates associated with the different versions of the weights.

Figure D.1: Estimating Retail Investor Influence wit Alternative Specifications: Correlation Analysis

This figure shows the correlations across our set of estimated weights over the period Jan 1963 to Dec 2023. $\hat{w}_t$ is the filtered weight from our main analysis. As described in Appendix D, $\hat{w}_t^*$ and $\hat{w}_t^\perp$ are, compared to the baseline model, estimated with an adjusted measurement equation, whereas $\tilde{w}_t$ excludes the deterministic part for the trend state-space model but leaves the measurement unaltered. $\hat{w}_t^L$ repeats the baseline estimation with a larger optimization grid. $\overline{w}_t$ represents the simple monthly average across the four aforementioned series. Finally, w_t^{FoF} is the weight based on Flow-of-Funds data, which corresponds to the blue line displayed in Figure 2. Panel A shows raw correlations, whereas Panel B considers correlations across the detrended series (residuals of a regression on time). Two-sided p-values are shown in parentheses.



(A) Raw Series



(B) Detrended Series

Table D.1: Estimating Retail Investor Influence with Alternative Specifications: Main Parameter Estimates

Version	w_0	γ	ϕ	$\overline{\hat{w}}$
	0.9928	-0.0007	0.2781	0.7309
$\hat{w}_t$	(0.902)	(0.008)	(0.000)	(0.000)
	(0.482)	(0.004)	(0.000)	(0.000)
	0.9516	-0.0006	0.4034	0.7334
$\hat{w}_t^*$	(0.646)	(0.212)	(0.000)	(0.034)
	(0.324)	(0.100)	(0.000)	(0.014)
	1.0827	-0.0012	0.3429	0.7081
$\hat{w}_t^\perp$	(0.528)	(0.018)	(0.004)	(0.000)
	(0.718)	(0.010)	(0.004)	(0.000)
	0.9020		0.2780	0.7816
$\tilde{w}_t$	(0.116)		(0.018)	(0.188)
	(0.094)		(0.018)	(0.188)
	0.9909	-0.0007	0.2801	0.7317
$\hat{w}_t^L$	(0.886)	(0.012)	(0.000)	(0.000)
	(0.476)	(0.008)	(0.000)	(0.000)

This table shows the Kalman filter estimates for the main parameters of interest, obtained under different modeling choices. $\hat{w}_t$ is the filtered weight from our main analysis. As described in Appendix D, $\hat{w}_t^*$ and $\hat{w}_t^\perp$ are, compared to the baseline model, estimated with an adjusted measurement equation, whereas $\tilde{w}_t$ excludes the deterministic part for the trend state-space model but leaves the measurement unaltered. $\hat{w}_t^L$ repeats the baseline estimation with a larger annealing grid. Point estimates are presented alongside their two and one-sided p-values in parentheses, which are computed empirically by bootstrapping under the null for each of the parameters as described in Appendix A.3. The two-sided p-values test individually the null hypotheses whether $w_0 = 1$, $\gamma = 0$, $\phi = 0$, $\overline{\hat{w}} = 0$. The one-sided p-values test the same, but against the alternative hypotheses that $w_0 < 1$, $\gamma < 0$, $\phi > 0$, $\overline{\hat{w}} < 1$.

E Estimating Investor Influence when Institutions are Irrelevant: Simulation Analysis

We conduct a simple simulation exercise to showcase that our Kalman-filtering procedure is able to recover a variety of latent processes with different properties. Precisely, we demonstrate that our procedure could recover estimates consistent with the null hypothesis of "institutional irrelevance" for market valuations. Recall the measurement equation:

$$dp_t = \beta \left[w_t EXP_t^{RI} + (1 - w_t) EXP_t^{PRO} \right] + \mu_t + \varepsilon_t.$$

To reflect the null, we set in the simulation $w_t = 1 \ \forall t$. Additionally, for simplicity, we assume that there is no latent process for discount rates ($\mu_t = 0 \ \forall t$), and that the household expectations explain fluctuations in the dp-ratio with a negative unit loading ($\beta = -1$). Hence, our simulated measurement becomes:

$$dp_t^f = -EXP_t^{RI} + \varepsilon_t^f \tag{E.1}$$

, where we draw $\varepsilon_t^f \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma_{\varepsilon^f}^2)$. Here, the value we choose for the variance of ε_t^f is arbitrary, and larger values make the measurements mechanically less informative of the true latent weights process. For this reason, we consider the most stringent case and set $\sigma_{\varepsilon^f}^2 = 0.17$ - which corresponds to the unconditional variance of dp_t in the data, and is used as an upper bound for R in the optimization grid from the main analysis.

We then repeat our entire Kalman-filtering strategy using dp_t^f as the measurement. In total, we draw 250 vectors for the measurement error and repeat the estimation procedure for the same number of iterations. The results are presented in Figure 9, where the solid line represents the median state estimate across simulations. The figure confirms the capacity of our filter to recognize that the true data generating process is constant over time, which is displayed as a dashed horizontal line. The filtered series in gray reflects that updates coming from the dp-ratio pull the estimates toward the true state — but the measurement error causes imperfect adjustments and fluctuations. Over the entire sample period the true weight is contained within the 95% shaded confidence bands, which are derived from the monthly standard deviation of the state estimates across simulations. In Table E.1 we show the accompanying parameter estimates, which echo the message from Figure 9: our Kalman filter recovers an intercept and average weight close to 1, and it recognizes that cyclical components and trend dynamics do not play a role in determining the measurements under the current set-up. All in all, the simulation results reassure us that our baseline model does not have a natural tendency to recover, e.g., processes with negative slopes.

Table E.1: Main Parameter Estimates Under Institutional Irrelevance

w_0	γ	ϕ	$\overline{\hat{w}}$
1.0201	-0.0001	0.1146	0.9357
(0.826)	(0.725)	(0.640)	(0.504)
(0.500)	(0.500)	(0.500)	(0.504)

This table shows the main parameter estimates for the filtered weights shown in Figure 9. Point estimates are presented alongside their two and one-sided p-values in parentheses, which are computed empirically by bootstrapping under the null for each of the parameters as described in Appendix A.3. The two-sided p-values test individually the null hypotheses whether $w_0 = 1$, $\gamma = 0$, $\phi = 0$, $\overline{\hat{w}} = 1$. The one-sided p-values test the same, but against the alternative hypotheses that $w_0 < 1$, $\gamma < 0$, $\phi > 0$, $\overline{\hat{w}} < 1$.

F Estimating Investor Influence with Noisy Expectations: Simulation Analysis

In our main estimation of the influence of households and professionals on asset prices, we treat expectations as quantities that are observed via survey instruments. However, survey data likely captures true investor expectations with noise.

Formally, let the observed retail and professional expectations series be noisy measures of latent expectations:

$$EXP_t^{RI} = \overset{*}{EXP}_t^{RI} + \nu_t^{RI} \tag{F.1}$$

$$EXP_t^{PRO} = \overset{*}{EXP}_t^{PRO} + \nu_t^{PRO} \tag{F.2}$$

where $\overset{*}{EXP}_t^{RI}$ and $\overset{*}{EXP}_t^{PRO}$ denote the true expectation processes, and EXP_t^{RI} and EXP_t^{PRO} denote the measured expectations. The distinction between actual and measured expectations can affect our results, since asset prices are driven by true latent expectations. In other words, the true law of motion of the dp ratio is as follows:[7]

$$dp_t \propto \beta^* \left[w_t^* \overset{*}{EXP}_t^{RI} + (1 - w_t^*) \overset{*}{EXP}_t^{PRO} \right] + \varepsilon_t^*. \tag{F.3}$$

whereas in our Kalman filter the measurement equation relies on the observed data.

$$dp_t \propto \beta \left[w_t EXP_t^{RI} + (1 - w_t) EXP_t^{PRO} \right] + \varepsilon_t. \tag{F.4}$$

As a result, noise in the measurement of expectations can create key discrepancies between the time-series of true investor influence w_t^* and the estimated one w_t.

The purpose of the simulation analysis in this section is to study the properties of recovered versus true influence weights under several scenarios of measurement error in survey expectations.

To implement the simulation, we must specify the latent expectation processes, the true path of the weights, the discount-rate component, and the amount of noise in both expectations and the measurement equation. We begin with the latent expectations processes, which we model as standard AR(1) processes. To calibrate these processes we need an educated guess about the properties of these autoregressive processes. One straightforward way to develop insights is to start from the assumption that the principal component of the retail and professional surveys shown in Panels B and C of Figure 1 is a good approximation to the true expectations process underlying

[7] For expositional simplicity, in this derivation we abstract from control variables , and we focus on the variation in the dividend–price ratio that is orthogonal to such variables.

each investor group. Using the time series of the survey principal-component measures shown in Figure 1, we fit AR(1) models separately to the retail and professional series. We then simulate $\overset{*}{EXP}_t^{RI}$ and $\overset{*}{EXP}_t^{PRO}$ so that they match the persistence, mean, and standard deviation observed in the data.

We next calibrate the noise in observed expectations. Following up on the intuition above, we use the residual variation from regressions of EXP_t^{RI} and EXP_t^{PRO} on their principal-component counterparts.[8] These regressions are used to calibrate the variance of the residuals in Equations F.1 and F.2, as well as the covariance between innovations in those two equations. Taken together, The steps above allow to construct simulated time-series of noisy expectations and true expectations that are consistent with data. We repeat the approach above to generate $s = 1, \ldots, 250$ simulated set of true and noisy beliefs.

The final step is to build, within each simulation, the dividend-price ratio as per Equation F.4. To that end, we need to select a time-series of the weights. Given that our goal is to compare estimated weights with the weights that would be observed under the null of no institutional influence, we concentrate on simulating Equation F.3 in the scenario in which only households matter for asset prices (i.e., $w_t^* = 1, \forall t$). In such a scenario, we ask whether noise in expectations could lead to the recovery of a time-series of household influence whose features resemble the ones uncovered in the data. Moreover, in keeping with the actual estimation conducted in the paper, the simulated dividend–price include a discount-rate component μ_t, which is based on the extracted time-series of that process in the main analysis. We also set $\beta^* = -1$, since the true and recovered magnitudes of β^* are not central for the exercise.

To calibrate the variance of ε_t^* in Eq. (F.3), which we assume to follow a standard normal distribution, we focus on the residual variation in the dividend–price ratio after conditioning on noisy expectations and discount rates. In the model above, this unexplained variation has two sources. First, observed expectations are noisy, so the fitted component based on survey expectations is only an imperfect proxy for the latent component that truly drives valuations. Second, the dividend–price ratio is subject to the additional disturbance ε_t^*. The first source of residual variation is already pinned down by simulating latent and measured expectations as described above. We therefore choose $Var(\varepsilon_t^*)$ so that, once noise in expectations is accounted for, the model reproduces the same unexplained share of the variance in the dp ratio as in the data. Let R^2 denote the fit of the regression of dividend-price on the noisy-expectations proxies as in Equation F.4, where the discount rate process is also included as a control in the regression. Define the unexplained share of variation in the regression as as $c = 1 - R^2$.

[8] Before estimating these regressions, we convert the principal-component series into return expectations using the linear-projection method in Greenwood and Shleifer (2014) and Barberis et al. (2015a). Specifically, we rescale the survey principal components by regressing EXP_t^{RI} and EXP_t^{PRO} on the principal-component time-series, using the fitted value as the rescaled principal component time-series.

For simulation draw s, define the fitted component based on observed expectations as

$$x_t^{(s)} = -\left[w_t EXP_t^{RI,(s)} + (1-w_t) EXP_t^{PRO,(s)}\right] + \mu_t, \tag{F.5}$$

and let the corresponding latent component be

$$x_t^* = -\left[w_t \overset{*}{EXP}_t^{RI} + (1-w_t) \overset{*}{EXP}_t^{PRO}\right] + \mu_t.$$

Because observed expectations differ from latent expectations only through measurement error, we can write

$$x_t^{(s)} = x_t^* + u_t^{(s)},$$

where $u_t^{(s)}$ captures the noise induced by ν_t^{RI} and ν_t^{PRO}. Similarly, the simulated dividend–price ratio satisfies

$$dp_t^* = x_t^* + \varepsilon_t^*,$$

with $x_t^* \perp \varepsilon_t^*$ and $u_t^{(s)} \perp \varepsilon_t^*$.

Define

$$V_x := Var(x_t^*), \qquad V_u := Var(u_t^{(s)}), \qquad V_\varepsilon := Var(\varepsilon_t^*).$$

Our calibration condition is

$$Var(dp_t^* \mid x_t^{(s)}) = c\, Var(dp_t^*). \tag{F.6}$$

This condition pins down V_ε because V_x is determined by the simulated latent process and V_u by the calibrated expectation noise, leaving V_ε as the only remaining unknown. Since

$$Var(dp_t^*) = V_x + V_\varepsilon$$

and

$$Var(dp_t^* \mid x_t^{(s)}) = Var(x_t^* \mid x_t^{(s)}) + V_\varepsilon = \frac{V_x V_u}{V_x + V_u} + V_\varepsilon,$$

it follows that

$$V_\varepsilon = \frac{cV_x - \dfrac{V_x V_u}{V_x + V_u}}{1-c}.$$

We use this expression to calibrate the variance of the innovations in the dividend–price in each simulation s.

Finally, having obtained within each simulation s a set of noisy expectations as well as a dividend–price ratio that is consistent with true expectations and the null of no-intermediary influence, we perform the same Kalman-filter estimation for each s. This leads us to obtain 250 time-series of the recovered weights $w_t^{(s)}$. The graphical evidence in Figure 10 summarizes the results. Furthermore, Table F.1 shows the main parameter estimates of interest.

Table F.1: Main Parameter Estimates Under Mismeasured Expectations

w_0	γ	ϕ	$\overline{\hat{w}}$
0.8135	0.0000	0.0935	0.8306
(0.6079)	(-0.0004)	(0.0344)	(0.7279)
(1.0371)	(0.0006)	(0.2106)	(0.9472)

This table shows the main parameter estimates for the filtered weights shown in Figure 10. Average parameter estimates are presented alongside the bottom and top decile of their distributions in parentheses, computed across simulations.