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

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Abstract

Intermediary asset-pricing theories predict that as households delegate investment decisions, professional investors increasingly determine market valuations. Existing tests typically rely on indirectly measured intermediary risk preferences and cross-asset comparisons that can confound intermediation with other forces. We propose a belief-based test in the US stock market, where delegation varies substantially over the last 60 years and investor beliefs are directly observed in surveys. We estimate a structural model in which retail and professional return expectations have time-varying, complementary effects on valuation, recovering a decades-long latent time series of each group's influence. Professionals' influence rises as delegation grows, yet retail investors remain more influential than implied by administrative measures of delegation. Influence shifts reflect temporary shocks linked to risk, and long-lived shocks that we connect to major regulatory, social, and market-structure events with the aid of a large-language model. A belief index incorporating our recovered influence series strongly predicts future stock market returns— resolving the weak predictability of survey expectations in prior work — and establishes a direct link between intermediary asset pricing and behavioral finance.

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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 filter 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.

[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).

2 A Structural Model of Market Valuation

2.1 Setup

A traditional view of market valuations in finance is that asset prices rise and fall based on changes in investors' risk appetite (i.e., discount-rate changes), or changes in expected dividend growth (Campbell and Shiller, 1988). Central to our empirical framework is the insight in recent theoretical and empirical work in behavioral finance indicating that price fluctuations can also be reconciled with variation in investor subjective expectations of future returns (e.g., Barberis et al., 2015a, 2018).

Our work begins by combining the above insights with recent work in intermediary asset pricing. This work 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 particular, recent work in this area proposes that in a fully non-intermediated market, or in a market in which the agency conflict between households as principals and intermediaries as agents can be contracted away, only households matter. The same is true in a market in which households promptly adjust their asset demand 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 quick portfolio adjustments are unlikely, or a market with severe agency concerns, intermediary asset-pricing theories posit that intermediaries and institutional investors, rather than households, contribute disproportionately to price determination.

Our empirical framework is built on the notion that, while households do delegate financial decisions to professionals, it is unknown to what extent such a delegation lends itself to the frictionless view above where professionals do not matter in the US stock market. To shed light on this, we rely on insights from behavioral finance linking asset valuation to investor subjective beliefs. Specifically, our goal is to estimate the following structural model of the dividend-price ratio of the market:

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

Simply put, like in previous work in behavioral finance, aggregate market valuation represented by the log dividend-price ratio comoves with investor subjective return expectations. Unlike the previous work in this area, our econometric model embeds the insights of intermediary asset pricing by allowing for a heterogeneous and possibly time-varying influence that

professional investors' expectations (EXP^{PRO}) on one hand, and households' expectations (EXP^{RI}) on the other, play in price formation. In particular, our model tracks who the relevant investor in the market is by means of the weight time series w_t: a higher w_t reflects a higher influence of households' expectations for price formation, while a lower value of w_t corresponds to a higher influence played by professional investors and financial intermediaries in the stock market. Importantly, we take the influence of these two broad types of market participants to be time-varying, so as to be able to capture variation in households' and professionals' influence that can possibly stem from changes in delegation, agency conflicts, and regulatory conditions that over time can alter whose beliefs are most relevant to explain market valuation. Equation (1) also includes a vector of control variables X_t, observed or unobserved, which we incorporate for consistency with prior work on the determinants of aggregate valuations.

Having deemed w_t as a latent state governing Equation (1), our goal is: (i) to recover estimates for this latent process via a Kalman-filtering approach; (ii) to link the uncovered 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 follow a Kalman-filtering approach (Kalman, 1960). The model, in which for consistency with prior work all observable quantities are demeaned and expressed in logs, features one measurement equation and two latent processes w_t and μ_t that are meant to capture the time-varying influence of retail investor beliefs on asset prices, and time series variation in an unobservable persistent discount-rate process, respectively:

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

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

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

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

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

In our structural model, the latent weight that describes the relative influence of households over professionals on the stock market follows a standard *trend plus cycle* specification that is common in macroeconomics, e.g., (Clark, 1987; Harvey, 1990; Harvey and Jaeger,

1993; Kuttner, 1994). The cyclical component u_t captures transitory variation in the influence of households, e.g., variation that could be ascribed to changes in broad economic conditions throughout the business cycle. Temporary variation in the influence of households on equity prices can arise due to variation in factors that moderate the link between households' expectations and demand for stocks, such as time-varying risk aversion, e.g., (Campbell and Cochrane, 1999), financial frictions, or to variation in attention, for instance due to market states, e.g., (Da et al., 2011; Karlsson et al., 2009).

The component τ of Equation 3 captures instead long-lived and possibly permanent shocks to the influence of households on financial markets. These shocks may occur, for instance, due to regulatory and legal reforms that permanently lead to a rise in professional investing, or due to events that promote permanent shifts in retail investors' direct participation in the market.[7]

Our modeling of τ includes a deterministic trend component, with slope equal to γ. Including this component in the model allows us to easily test the conjecture that retail investors' influence on asset prices may have declined over the last 60 years, possibly owing to a slow but continuous rise in the extent of delegation (French, 2008; Stambaugh, 2014b). If this is the case, we expect the coefficient $\gamma < 0$. Importantly, the view that households' influence may have diminished over time contrasts with a frictionless view of the delegation process, whereby households are the ultimate owners of the market, and their actions and beliefs are ultimately what shapes asset prices (Cochrane, 2011; Santos and Veronesi, 2022). To the extent that this second view is supported by the data, the delegation process does not diminish or change the impact of households' beliefs on asset prices, i.e., $\gamma = 0$. Given these two opposing views, we let the data speak and can easily summarize our result by means of the estimate of coefficient γ.[8]

The model of retail investors' influence on market valuation also features an intercept w_0. This intercept is meant to capture the influence of retail investors on the stock market at the beginning of the sample in 1963. Jointly with the other components of the model, this parameter allows us to accommodate the frictionless view of financial markets we alluded to before. In such a view, $w_0 = 1$, i.e., households have full influence on the market, and $\gamma = 0$, i.e., despite growing delegation, there is no deterioration in households' influence. Of course, by recovering the time series variation in households' influence, our econometric framework

[7]Later, in Section 5.2, we perform an analysis that explicitly links major events in the regulatory, competitive, and social landscape of the US stock market to the variation in τ.

[8]Importantly, as we later show via simulations (Appendix E), our econometric approach need not recover a negative trend, and it would recover a stable time-series of w_t hovering around 1 if the null hypothesis of no-intermediary influence was borne in the data. Thus, our model can provide an unbiased, data-driven estimate of whether the historical erosion of households' influence in the stock market that is advocated by past work is truly supported by the data.

can do more than just infer the parameters above, and it can inform quantitatively about how close households' influence is to the frictionless view at any point in time in recent US history.

Finally, in the spirit of Van Binsbergen and Koijen (2010) and Cochrane (2011), we include a discount-rate process μ_t in Equation 2.[9] As is standard, we assume an AR(1) structure. In the next section, we provide a detailed overview of the exact equations and assumptions.

2.3 Model Estimation

To estimate the model, we rewrite the measurement equation as follows:

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

where

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

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

As it is standard, and following our model, we rewrite the state-vector as follows:

$$x_t = F x_{t-1} + c + G\Sigma_t. \tag{6}$$

with

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

[9] We instead abstract from modeling an underlying process for expected dividend growth, because most previous literature finds that variation in the dividend-price ratio is not driven by variation in rational expectations of dividend growth. Including this component in the model also allows us to reconcile the persistence in the dividend-price ratio that is difficult to reconcile based on the dynamics of return expectations (e.g., Nagel and Xu, 2022).

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

and

$$\Sigma_t \overset{\text{iid}}{\sim} \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, Q \right), \qquad Q = \begin{bmatrix} \sigma_\zeta^2 & 0 & 0 \\ 0 & \sigma_\eta^2 & 0 \\ 0 & 0 & \sigma_\xi^2 \end{bmatrix}. \tag{7}$$

The state vector x_t captures the time-series of interest that we seek to recover. In particular, the first two components of the vector concern the permanent and transitory components of retail investors' influence τ_t and u_t, while the third component concerns the discount rate, modeled as an AR(1) process following previous work. The state-vector follows a convenient autoregressive behavior as in Equation 6. The transition matrix reflects the model architecture, and shocks in the model are taken to be orthogonal to each other, i.e., matrix Q is diagonal.

We use the Kalman filter to estimate the model via maximum likelihood. The main outcome of the model estimation is the recovered time-series $\hat{w}_t$, as well as the vector of model parameters $\theta = [w_0, \gamma, \phi, \rho]$.

Estimation via Kalman filters requires starting values for the latent states, as well as a stated level of uncertainty over such values and first guesses of the parameters in the model. These are summarized in Table 1, which provides also a rationale for each of the choices made in the estimation setup. For some key model parameters, most notably the variance of the error terms in the measurement equation, and the variance of the error term governing the transitory component of retail investors' influence, there is no clear guidance ex-ante. Thus, our estimation involves a simulated-annealing (SA) strategy. In short, the SA approach entertains several combinations of σ_ϵ^2 and σ_η^2. For each such combination we estimate the model, collect model parameters and the filtered time-series $\hat{w}_t$, and then combine such individual estimates based on rank-weighted model solutions. The ranking is based on the value of the log-likelihood function, so that better-fitting solutions hold larger influence on the final outcome we report, while still acknowledging model uncertainty. Appendix A.2 provides a detailed description of the entire estimation procedure.

Finally, to provide confidence interval for the estimated model parameters, as well as for the time-series of our recovered weights, we implement a residual bootstrap procedure. 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. The details on the bootstrapping procedure can be found in Appendix A.3.

3 Data

Several sources of data are needed to perform our analysis. First and foremost, we need time-series data on the expectations of retail investors and professional investors, 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.[10] 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

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

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 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:[11]

$$\begin{aligned} \text{EXP}_{gt}^{RI} &= a_g + b_g \sum_{j=1}^{15} w_{gj} R_{(t-j+1)} + \epsilon_{gt} \\ w_{gj} &= \frac{(\lambda_g)^{(j-1)}}{\sum_{k=1}^{15} (\lambda_g)^{(k-1)}} \ , \end{aligned} \tag{8}$$

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 2 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}:

[11] 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.

$$
\begin{aligned}
EXP_t^{RI} &= \overline{a_t} + \overline{b_t} \sum_{j=1}^{15} w_j R_{t-j+1} \\
w_j &= \frac{(\overline{\lambda_t})^{(j-1)}}{\sum_{k=1}^{15} (\overline{\lambda_t})^{(k-1)}} \quad , \\
\overline{a_t} = \frac{\sum_{g=1}^{5} \widehat{a_g} DH_{g(t-1)}}{\sum_{k=1}^{5} DH_{k(t-1)}}, &\quad \overline{b_t} = \frac{\sum_{g=1}^{5} \widehat{b_g} DH_{g(t-1)}}{\sum_{k=1}^{5} DH_{k(t-1)}}, \quad \overline{\lambda_t} = \frac{\sum_{g=1}^{5} \widehat{\lambda}_g DH_{g(t-1)}}{\sum_{k=1}^{5} DH_{k(t-1)}}
\end{aligned}
\tag{9}
$$

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:

$$
DH_{gt} = N_{gt}^{HH} \pi^D{}_{gt} \overline{DH_{gt}} \tag{10}
$$

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.[12]

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.

[12]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 9. 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.[13] 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.[14] As we show in the next section, the II survey comoves heavily with other expert surveys, thus we use it as the longest readily available proxy of professional beliefs in our sample. 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.[15]

3.2 Survey 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:

[13] 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.

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

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

(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.[16] 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 (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[17], and (iii) survey data from the American Association of Individual Investors. This principal component is intended to capture the time-series variation in the

[16] 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.

[17] 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).

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.[18]

The results, in Table 3, 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 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.

[18]Working with changes in beliefs is the natural choice here. Conceptually, flows reflect changes in demand that are naturally linked to revisions in expectations, rather than expectations levels (e.g., Berk and Green, 2004). Econometrically, fund flows in our sample are known to display non-stationary behavior such as a pronounced negative trend. With trending or highly persistent series, finite samples can exhibit spuriously large correlations even when the underlying processes are independent (Granger and Newbold, 1974).

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 (2014), 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 C 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

Our empirical approach, which uses survey-based expectations of retail and institutional investors in a structural model of latent market impact, ultimately delivers estimates for the time-varying influence that households exert on asset prices. In Figure 2, we present the time series of these estimates in gray. Confidence intervals are obtained via bootstrapping. In Table 5 we report the parameter estimates obtained from the Kalman filter, as well as their bootstrapped distribution. Finally, in Figure 3 we perform hypothesis testing, as we compare the estimates obtained from the data with their bootstrapped counterparts obtained under the null of no influence for intermediaries throughout the sample (i.e., $w_0 = 1$, $\gamma = 0$, $\phi = 0$).

Figure 2 reveals several interesting facts with respect to the degree of household influence on stock prices over time. First, at the beginning of the sample period, households exert most of the influence on market valuation, i.e., households' influence at that time, captured by the parameter w_0 in our model, is close to one. This implies little to no role played by intermediaries and professional investors in the early 1960s. In that period, both administrative data on households' portfolios, and past research note that the stock market was almost entirely non-intermediated as households held stocks mostly directly. As a matter of fact, panel A of figure 3 shows that we cannot reject the null of full households influence at the beginning of the sample (i.e., $w_0 = 1$).

Second, the time-series of investor influence depicted in 2 is heavily downward sloping. The most straightforward way to quantify this decline, and to assess whether the decline is a statistically significant fact, is to focus on the deterministic trend *gamma*. The distribution of γ in 5 shows that the negative sign of this coefficient is a rather stable feature across bootstrapped samples of the data. Moreover, Panel B of Figure 3 shows that, if γ was zero in the data (i.e., if there was no deterioration of households' influence over time), there would be only a 0.2% probability of estimating a value of this parameter as large and negative as the one we recover from the Kalman filter. Not only the decline that we uncover is statistically significant, but also economically important: as the figure 2 shows, over the course of the last 60 years, retail investors' influence has declined from 1 to roughly 0.5, a meaningful 50% decline.[19]

The third fact that figure 2 comes from a comparison of our recovered time-series of retail investor influence, with the time-series of Households' direct ownership of stocks, also

[19] A back-of-the envelope calculation shows that the estimated weights decrease approximately by $\hat{\gamma} \times T = -0.0007 \times 732$ months $= -0.5124$.

reported in the figure. Whereas both households' direct participation in the market and households' influence experience a decline in our sample, households' influence is always higher throughout the sample than what would be warranted by households' direct involvement in the market. Said differently, even though households switch progressively more from direct ownership of stocks to indirect (i.e., intermediated) ownership over time, indirect ownership does not erase entirely households' influence, possibly owning to the contractual and fiduciary obligations that align professionals' behavior to households' preferences and beliefs.

Finally, Figure 2 shows that for a very large portion of the sample we are able to reject the null of no-intermediary influence (i.e., a value of retail investors' influence equal to 1), in that this value lies outside of the confidence intervals of $\hat{w}_t$ in 86% of the sample months (or about 50 years). As a formal test of whether, overall, we can reject the null of no-intermediary influence, Panel D of Figure 3 compares the average value of retail investor influence that we recover from the data (0.732), with the average influence that would be recovered under the null. The panel shows that if the data consistent with the null, we would on average recover a weight that is equal to one. More importantly, under the null, the probability of recovering an average retail influence that is small as the one we estimate would be close to zero.

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 trend (i.e., permanent) component of households' influence. Figure 4 visualizes this idea by means of showing a trend-cycle decomposition of our filtered weights. Panel (A) plots the trend in the form of the stochastic component of our drift process, $\tilde{\tau} \equiv \hat{\tau}_t - \hat{\gamma}t$, whereas panel (B) displays the transitory variation in the weights; $\hat{u}_t$. As noted before, the panels show the general property that on average the long-term variation in household influence is around one order of magnitude larger than the transitory variation. 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 start our examination of the variation in retail influence by zooming in on the transitory component of the filtered weights as displayed in Figure 4, panel (A). We conduct standard regression-based tests where we project the cyclical component of our filtered weights, $\hat{u}_t$, on

different sets of explanatory variables that could plausibly explain the time variation that we observe for the estimated series. The results are presented in Table 6.

In Panel A we try to explain the cyclical variation in retail investor influence through measures related to risk and investor risk preferences. The first measure we consider in this category is the Surplus Consumption Ratio (SCR) by Campbell and Cochrane (1999), which measures current levels of consumption relative to some habit level for households. Translated to risk-preferences, a drop in SCR indicates that current consumption moves towards the habit level, making households more risk averse and increasing risk premia. In other words, higher levels of SCR are associated with episodes of higher risk-tolerance for households. Consistent with this interpretation, we find a positive and statistically significant coefficient when regressing the cyclical component of household influence on the SCR. Precisely, a 1 standard deviation increase in SCR increases the temporary influence of households on prices by around 0.241 (t = 3.31). This is in line with the idea that, when households become more risk tolerant, their participation — and therewith their influence — in the stock market increases (Santos and Veronesi, 2022).

The next explanatory variable we test is REC, which is a binary variable that takes the value of 1 for months flagged as NBER recession periods. Contrary to the SCR, we obtain a negative slope estimate for REC in the univariate cycle regression. Economically, this makes sense, given that recession periods are commonly characterized by elevated levels of financial distress and risk-aversion, which in turn could lead to a decrease in equity market participation by households. Our regression shows that in recession months, the influence of retail investors on prices is on average 0.61 standard deviations lower than in non-recession periods. Even though this result sounds intuitive, it is ex-ante unclear what the net impact of a recession period would be in terms of relative market influence by households versus institutions, as it affects both players. We attach a similar interpretation to the negative slope (-0.138) we find when regressing $\hat{u}_t$ on the 12-month trailing of stock returns (VOL), although this result is slightly weaker in terms of statistical significance (t = -1.89) than for REC (t = -2.40).

Finally, Panel A considers two measures for the extent to which intermediaries are financially constrained, in the form of the Intermediary Capital Ratio (ICR, He et al., 2017) and broker-dealer Leverage (LEV, Adrian et al., 2014). The rationale behind including these variables into the analysis is that the risk-bearing capacities of institutions could affect the degree to which households can affect prices. For instance, a loosening of leverage constraints for financial intermediaries could entail a positive shock to their ability to exert market influence[20], as it frees up capital that in turn can be allocated to equities. Relatively speaking, a

[20]The direction of this prediction crucially depends on the cyclicality assumption for the leverage variable

shock that does not affect households and increases (decreases) the risk-bearing capacities of intermediaries, is under our modeling assumptions expected to decrease (increase) household influence. However, in terms of transitory price influence we find little evidence supporting this notion, as neither ICR nor LEV significantly explains variation in short-lived cycles of retail investor influence.

In panel B of Table 6 we test whether variables related to Household Finances could help explain the transitory fluctuations in retail investor influence on the US stock market. We first test the aggregate households' debt-to-income ratio (DTI), reflecting the idea that increases in income and leverage might increase participation, as described in Santos and Veronesi (2022). Our results indicate that higher levels of DTI are indeed associated with increased household influence, although the slope estimate is relatively small (0.066) and not statistically significant (t = 1.59). We obtain a slightly stronger result when we instead regress $\hat{u}_t$ on the employment-to-population ratio (EPR), which measures the fraction of the labor force to the entire US population at a monthly horizon. Our motivation for testing the EPR is that being employed could help overcome standard entry barriers faced by households, such as brokerage fees and transaction costs, that arise as a consequence of participating in the equity market (e.g., Favilukis, 2013). Consistent with this theory, we find a positive slope in the univariate regression (0.086) that is statistically different from 0 at the 5% level (t = 2.25). Hence, when a larger fraction of the population is employed — and can afford the costs associated to equity investing — we see an increase in the influence of households on prices that could be explained by higher levels of participation.

Other than for DTI and EPR, we do not find strong results for the other Household Finances variables that we consider in a statistical sense. In other words, the fraction of households that perceive their financial conditions as worse compared to one year ago (PFDET), their personal dividend income (PDI), nor their equity-to-financial (ETA) ratios, substantially help to explain cyclical variation in the market power of retail investors. The same applies for the Attention variables we consider in Panel C. Here, we record several measures that assess market conditions by comparing current quarter's (Q) or year's (Y) compounded return to the historical distribution of market performance. Precisely, we create binary variables that take a value one when the current period's compounded return is in the top quintile (20) or decile (10) of the time-series distribution of absolute market returns, or when the return is positive (POSRET). All in all, we do not find clear evidence that these measures of attention explain when, or to what extent, retail investors can influence market valuations.

We repeat the regression tests from Panels A to C for a 12-month horizon, where we take

under consideration.

the annual rolling average of $\hat{u}_t$ as the LHS variable and consider annual differences in the RHS variables whenever they display non-stationary properties. The results are presented in Panels D to F. Taken all together, the relationships that we recover are overall similar to the ones from the 1-month horizon tests, and in general the longer horizon version tends to give slightly stronger results.

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.[21] 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 Table B.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

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

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 leftmost column of Table B.1 provides a brief rationale for each one of the classification choices that we make.[22]

The second approach to the classification involves a large-language model. Specifically, for each candidate event we construct a self-contained textual description that states the nature and consequences of the event. This is obtained by merging an initial description prepared manually with an LLM-based one. Ultimately, we rely on the LLM to fulfill the requirement that 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 task.[23] We then use the OpenAI API to access the processing capabilities of GPT-o4 mini, a 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.

Finally, we also consider a combination of the manual and the LLM-based classifications, in which an event is flagged as positive or negative for retail investors' influence if both classifications agree, otherwise the event is flagged as ambiguous and it is not used in the following analysis.

5.3 Results

We use the classification 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 link 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.

[22] In fifteen cases, we find it difficult to clearly flag an event as positive or negative for retail influence. We classify such events as ambiguous, and do not use them in our analysis.

[23] For the step described in this subsection, we rely on OpenAI ChatGPT 5.2 thinking model.

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 instance, in Panel C which presents results using the reasoning LLM-based classification, we show that the documented effects are statistically significant, and their difference Δ is 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 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-filter 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.

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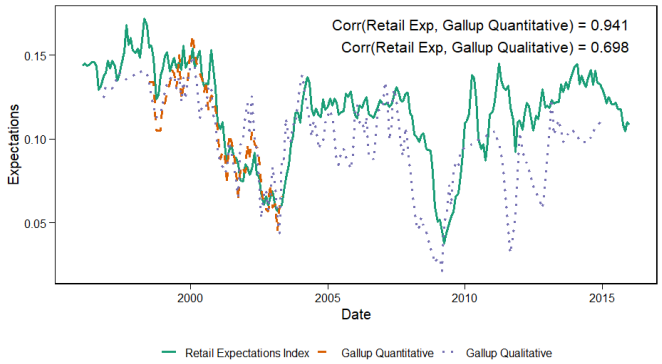
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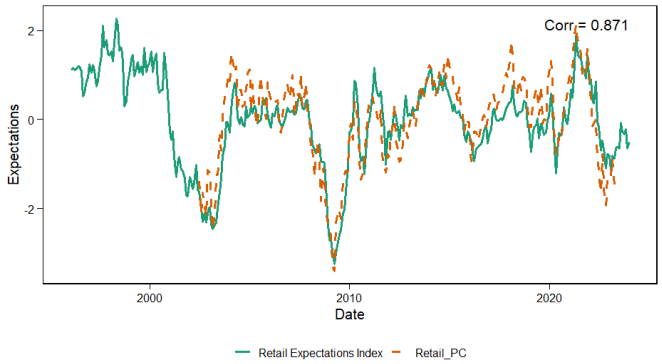
Figures

Figure 1: Investor Expectations - Validation

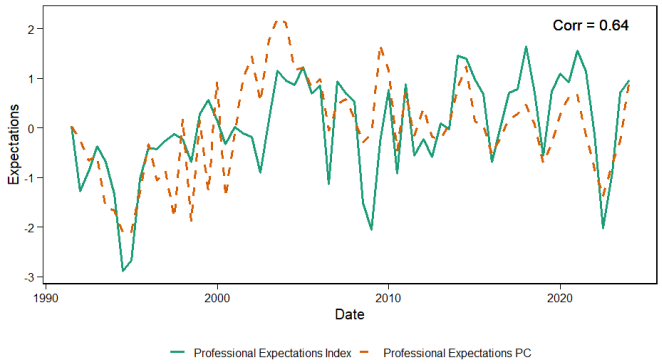
In panel (A), we overlay the time-series of our proposed retail-investor expectations index EXP^{RI} against quantitative and qualitative data on beliefs from Gallup, with the former available over the sample period 1998-2003, and the latter available to us with gaps over the sample period 1996-2015. 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 90% 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).

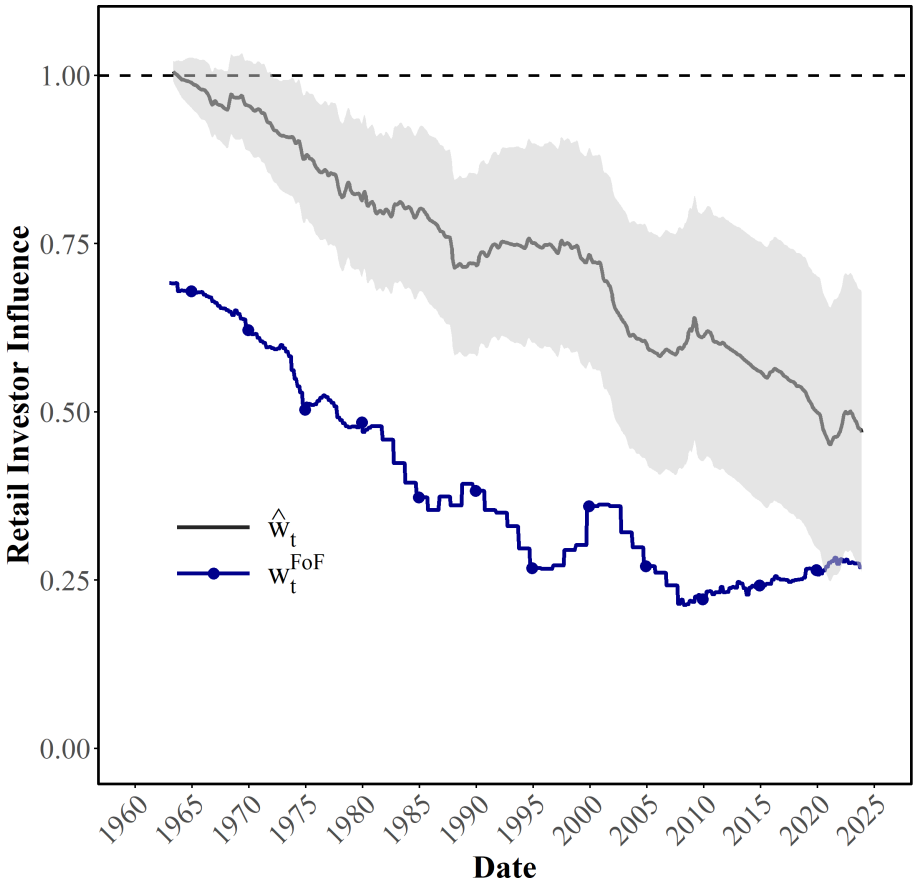
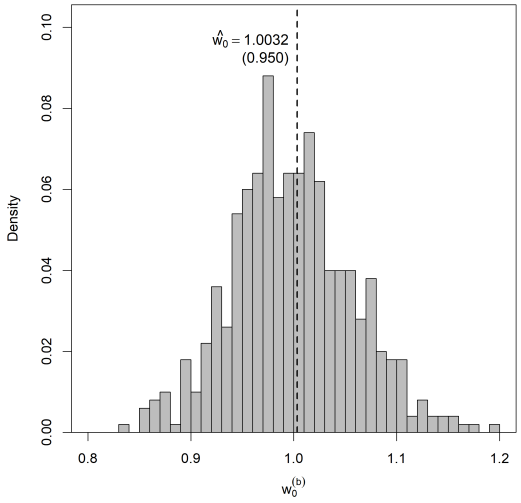
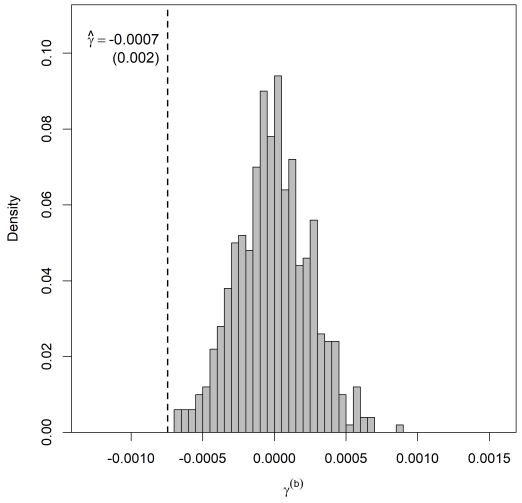


Figure 3: Retail Investors' Stock Market Influence - Hypothesis Testing

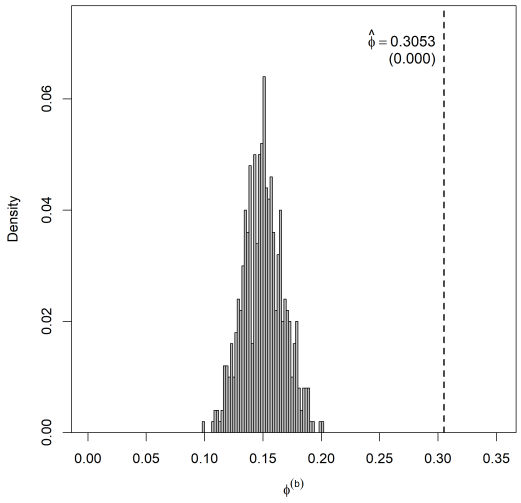
This figure plots the bootstrap distributions for the quantities of interest coming out of our Kalman filtering procedure. Panels (A) - (C) show the distributions of parameter estimates when measurements of the dp-ratio are simulated by holding these parameters jointly fixed at their assumed null values. We obtain the distributions via a bootstrapping procedure, where we sample 10 time-series blocks with replacement from the empirical distribution of residuals. Each of the graphs is based on $B = 500$ bootstrap iterations and includes the actual point estimates coming from Kalman filter, where the dashed lines indicate its positions relative to their bootstrapped distribution. Alongside the point estimates the two-sided p-values are presented in parentheses, which are computed empirically from the bootstrap distribution as explained in detail in Appendix A.3. The two-sided p-values test the point estimates against their null hypotheses, which assume that $w_0 = 1$, $\gamma = 0$, $\phi = 0$, for panels (A), (B), and (C), respectively. In panel (D) we plot the averages of the simulated weights themselves across bootstrap samples, in comparison to the mean weight estimate we obtain from our Kalman filter. The two-sided p-value in this panel tests whether $\bar{\hat{w}} = 1$, in other words, whether on average the estimated weights do not tend to move away from the unit intercept assumed under the null over the sample period Jan 1963 to Dec 2023.



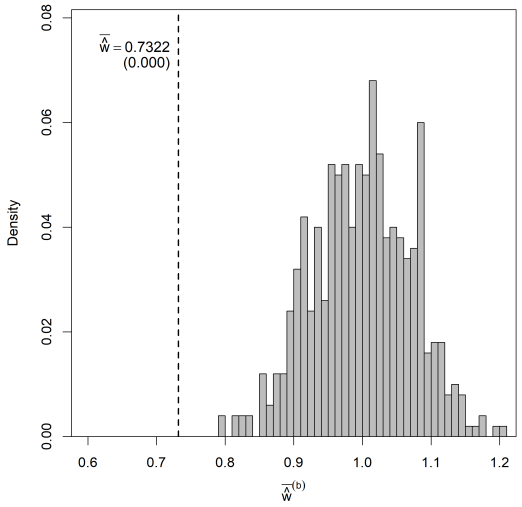
(A) w_0



(B) γ



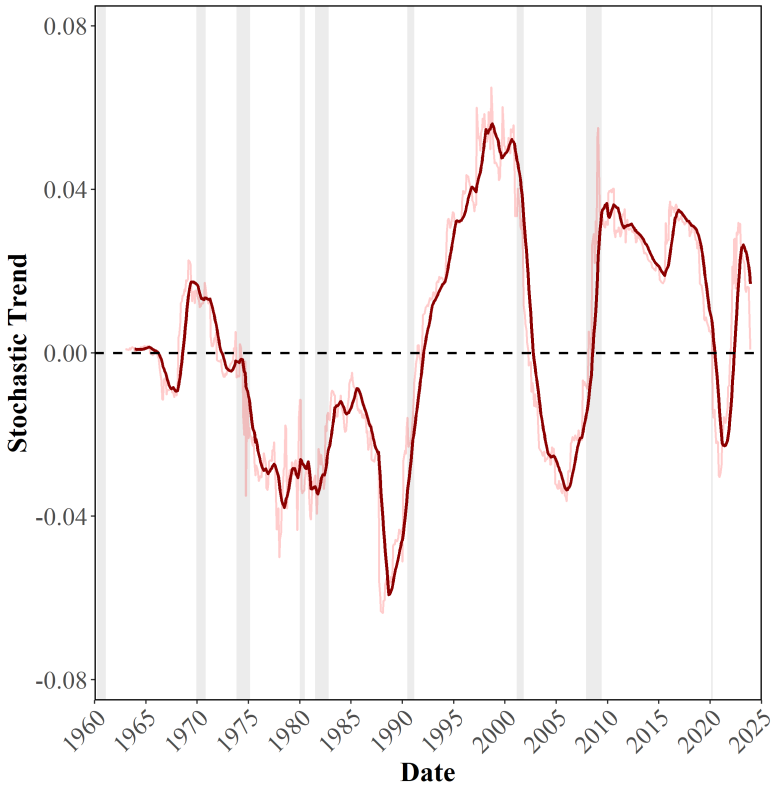
(C) ϕ



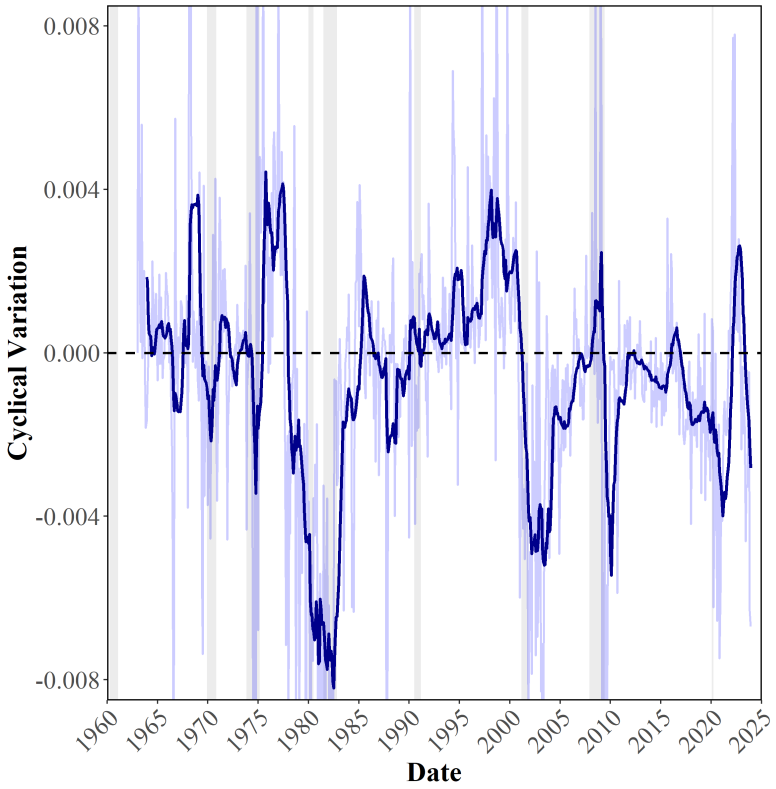
(D) $\bar{\hat{w}}$

Figure 4: Decomposing Retail Investor Influence

This figure visualizes the transitory and permanent shocks to the retail investor influence. Panel (A) plots the stochastic trend component; $\tilde{\tau}$, whereas panel (B) displays the transitory cycle component $\hat{u}_t$ of the estimated weights from our Kalman filter. 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) $\tilde{\tau}_t$



(B) $\hat{u}_t$

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 potential explanatory variables, tested 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 we observe a value of one.

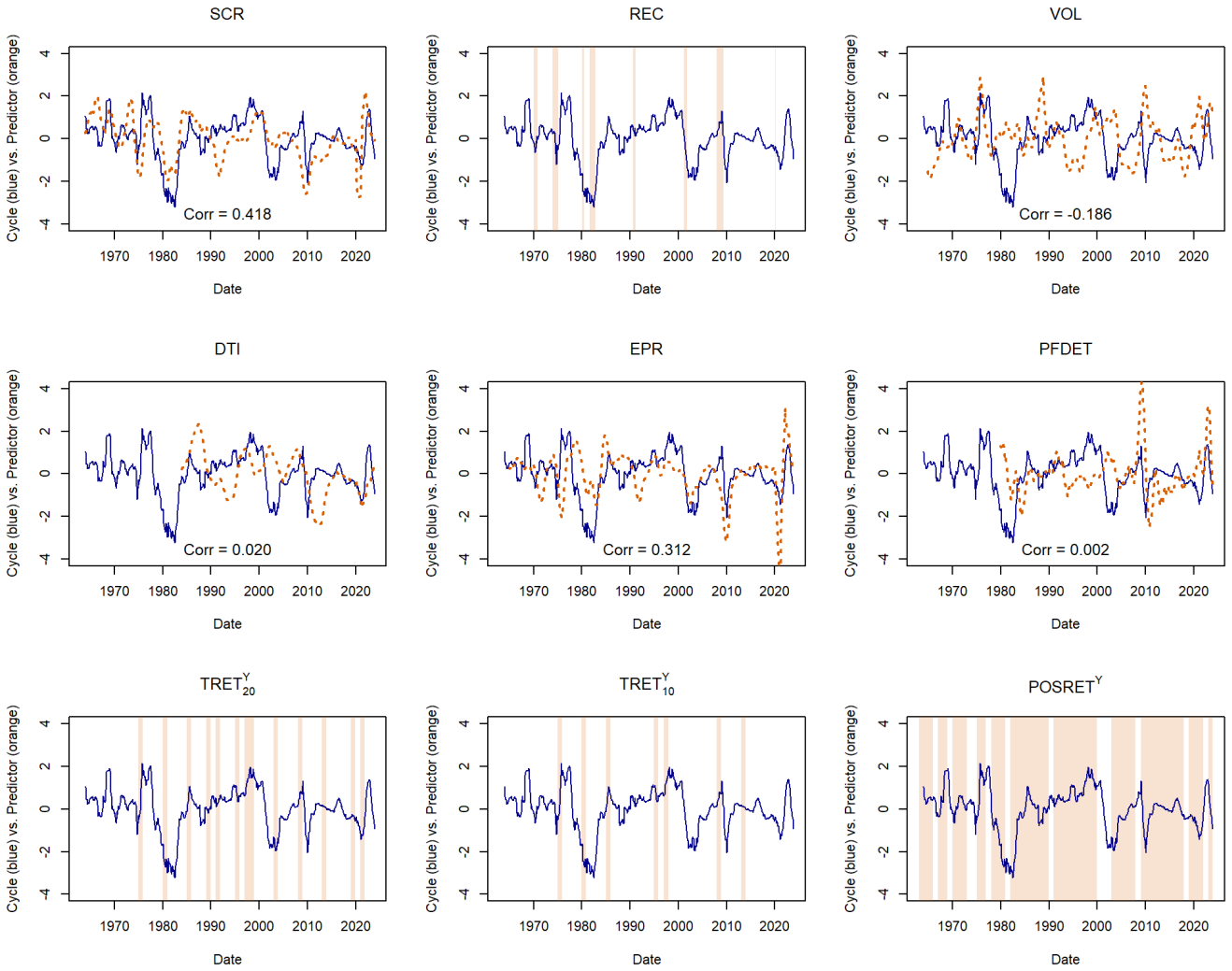
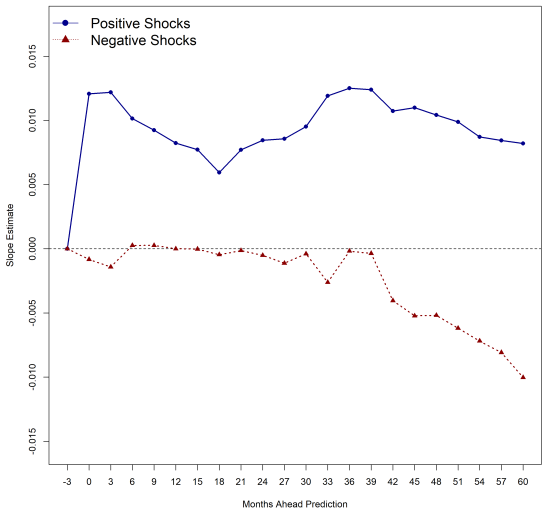
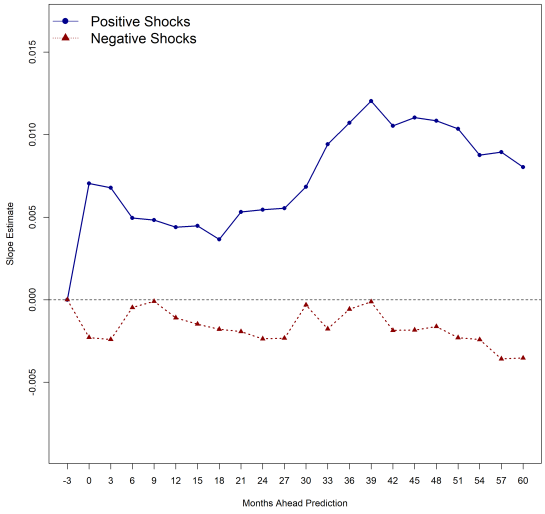


Figure 6: Explaining The Trend in Retail Investor Influence

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).

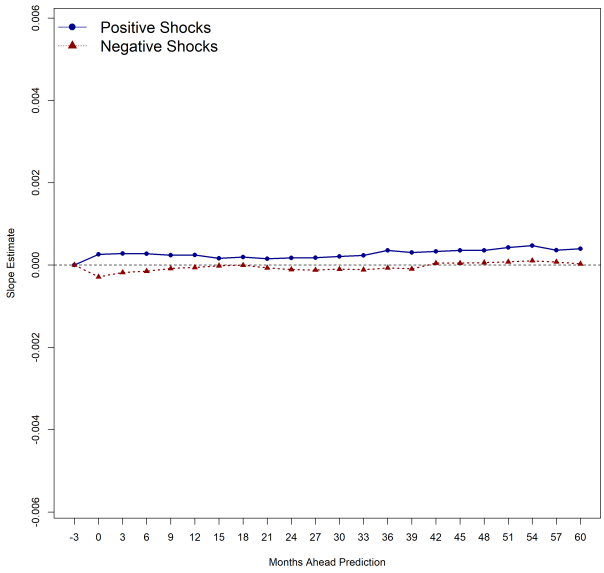


(A) Manual Classification

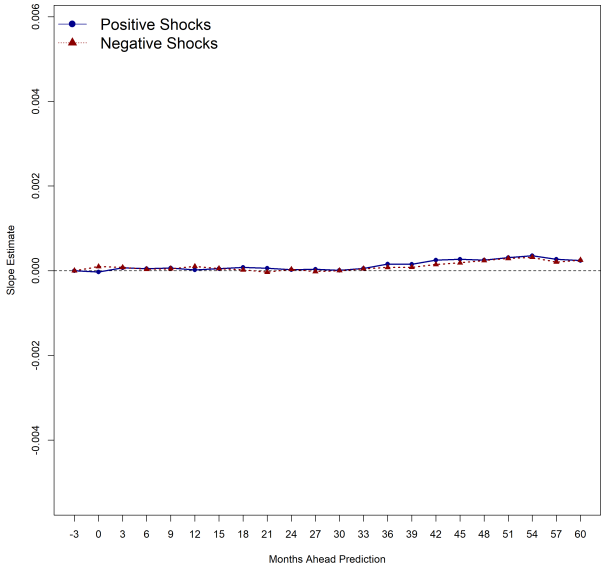


(B) LLM-based classification

Figure 7: Explaining The Trend 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 GPT-4o 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



(B) GPT-4o mini

Tables

Table 1: 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	The influence or retail investors at the beginning of the sample	1.000	Selected to capture the null of no influence by professionals.
τ_0	The trend component of retail investors' influence at the beginning of the sample	0.000	Set to zero, so w_0 easily maps on w_t at the beginning of the sample.
u_0	The 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	the 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	The constant 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^2_ε	Variance of innovations in the measurement equation	$\{0.010, ..., R\}$	A range of possible values is considered as part of a simulated annealing procedure. Grid contains 5 evenly spaced points. More details are in the Appendix A.2.1.
σ^2_η	Variance of transitory shocks in w_t	$\{0.250, 0.500, ..., v\} \times \sigma^2_\varepsilon$	Set to a multiple of σ^2_ε for the annealing, with $v = \frac{1}{R^{max}} \approx 6$. Grid contains 24 evenly spaced points, so total grid search is over 120 $(\sigma^2_\varepsilon, \sigma^2_\eta)$ combinations.
σ^2_ζ	Variance of innovations in τ_t	5×10^{-4}	Calibrated to reduce the likelihood that w_t falls outside of the interval [0,1]. More details are in the Appendix A.2.1.
σ^2_ξ	Variance of innovations in μ_t	0.023	Based on Van Binsbergen and Koijen (2010).
$P^{(1,1)}_{0\|0}$	Initial uncertainty for τ_0	0	No uncertainty on τ_0, such that w_0 pins down the initial level of w_t.
$P^{(2,2)}_{0\|0}$	Initial uncertainty for u_0	0.250	Based on feasible range of the weights as described in Schneider and Georgakis (2013): $((0.500 \times (max(w_t) - min(w_t)))^2 = 0.250$.
$P^{(3,3)}_{0\|0}$	Initial uncertainty for μ_0	0.175	Set to long-run variance of the process, $\frac{\sigma^2_\xi}{(1-\rho^2)}$ based on estimates in Van Binsbergen and Koijen (2010).

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

Table 2: 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
Observations	40	40	40	40	40

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 3: 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 4: Summary Statistics

Variable	Mean	Std	Min	Max	Periodicity	Obs	Sample	Source	Description
Panel A: Kalman 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: Explanatory 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 5: Kalman Filter - Estimation Results

Par.	Kalman Filter	Bootstrapped Distribution					
	Estimates	Mean	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
β	-0.5465	-0.5955	-0.8159	-0.7028	-0.6055	-0.4899	-0.3917
w_0	1.0032	1.0715	0.9405	0.9723	1.0053	1.0367	1.0699
γ	-0.0007	-0.0134	-0.0012	-0.0009	-0.0007	-0.0005	-0.0003
ϕ	0.3053	0.3535	0.3467	0.3517	0.3554	0.3587	0.3626
ρ	0.9573	0.8739	0.8171	0.8538	0.8830	0.9052	0.9193
σ_ε^2	0.0800	0.0841	0.0841	0.0841	0.0841	0.0841	0.0841
σ_η^2	0.2144	0.2586	0.2577	0.2577	0.2577	0.2577	0.2577

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).

Table 6: Explaining Cyclical Variation in Retail Investor Influence

Panel A: Risk and Risk Preferences						Panel B: Household Finances						Panel C: Attention					
SCR	0.241					DTI	0.066					$TRET_{20}^{Q}$	-0.19				
	[3.31]						[1.59]						[-1.25]				
REC		-0.607				EPR		0.086				$TRET_{10}^{Q}$		-0.115			
		[-2.40]						[2.25]						[-0.49]			
VOL			-0.138			PFDET			-0.03			$TRET_{20}^{Y}$			0.159		
			[-1.89]						[-0.72]						[0.93]		
ICR				0.025		PDI				-0.004		$TRET_{10}^{Y}$				0.268	
				[0.50]						[-0.17]						[1.12]	
LEV					0.019	ETA					0.026	$POSRET^{Y}$					0.168
					[0.52]						[0.43]						[1.02]
$Adj.R^2$	5.69	3.66	1.79	-0.09	-0.13		0.35	0.60	-0.08	-0.14	-0.07		0.45	-0.02	0.29	0.60	0.34
Observations	732	732	721	647	594		522	731	551	731	729		732	732	732	732	732

Panel D: Risk and Risk Preferences						Panel E: Household Finances						Panel F: Attention					
SCR	0.304					DTI	0.08					$TRET_{20}^{Q}$	-0.362				
	[2.72]						[1.27]						[-2.19]				
REC		-0.769				EPR		0.244				$TRET_{10}^{Q}$		0.010			
		[-2.25]						[2.63]						[0.05]			
VOL			-0.165			PFDET			0.122			$TRET_{20}^{Y}$			0.046		
			[-2.38]						[1.54]						[0.20]		
ICR				0.074		PDI				-0.004		$TRET_{10}^{Y}$				0.235	
				[0.85]						[-0.17]						[0.77]	
LEV					-0.051	ETA					0.064	$POSRET^{Y}$					-0.030
					[-0.60]						[0.71]						[-0.13]
Adj. R^2	9.26	6.03	2.58	0.36	0.07	Adj. R^2	0.84	5.83	1.24	-0.06	0.27	Adj. R^2	1.99	-0.14	-0.10	0.43	-0.12
Observations	721	721	721	636	585	Observations	489	720	540	720	720	Observations	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. Panel 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

	(1)	(2)	(3)	(4)
Positive Shock	0.009		0.008	0.008
	[1.83]		[1.75]	[1.68]
	(0.068)		(0.081)	(0.093)
	(0.034)		(0.040)	(0.047)
Negative Shock		-0.010	-0.010	-0.010
		[-2.25]	[-2.18]	[-2.03]
		(0.025)	(0.029)	(0.043)
		(0.012)	(0.015)	(0.022)
Δ			0.018	0.018
			(0.013)	(0.017)
R^2	0.004	0.006	0.009	0.011
#Events	36	31	67	75
Observations	672	672	672	672

Panel B: General Purpose LLM Classification

	(1)	(2)	(3)	(4)
Positive Shock	0.006		0.006	0.006
	[1.35]		[1.31]	[1.33]
	(0.177)		(0.191)	(0.183)
	(0.089)		(0.096)	(0.091)
Negative Shock		-0.004	-0.003	-0.003
		[-1.04]	[-0.98]	[-0.94]
		(0.299)	(0.327)	(0.350)
		(0.149)	(0.163)	(0.175)
Δ			0.009	0.009
			(0.121)	(0.121)
R^2	0.001	0.001	0.002	0.005
#Events	27	39	66	75
Observations	672	672	672	672

Panel C: Reasoning LLM Classification

	(1)	(2)	(3)	(4)
Positive Shocks	0.008		0.008	0.009
	[2.40]		[2.37]	[2.52]
	(0.016)		(0.018)	(0.012)
	(0.008)		(0.009)	(0.006)
Negative Shocks		-0.004	-0.004	-0.004
		[-0.88]	[-0.79]	[-0.80]
		(0.379)	(0.432)	(0.424)
		(0.190)	(0.216)	(0.212)
Δ			0.012	0.012
			(0.051)	(0.036)
R^2	0.004	0.001	0.005	0.013
#Events	40	33	73	74
Observations	672	672	672	672

Panel D: Classifications Combined

	(1)	(2)	(3)	(4)
Positive Shocks	0.009		0.009	0.008
	[1.98]		[1.88]	[1.73]
	(0.048)		(0.061)	(0.084)
	(0.024)		(0.030)	(0.042)
Negative Shocks		-0.011	-0.010	-0.011
		[-2.67]	[-2.59]	[-2.64]
		(0.008)	(0.010)	(0.008)
		(0.004)	(0.005)	(0.004)
Δ			0.019	0.019
			(0.001)	(0.002)
R^2	0.003	0.005	0.008	0.011
#Events	24	26	50	75
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 B.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 several ways: manually (Panel A), using an LLM with limited reasoning capabilities (GPT 4.1, Panel B), using an LLM with reasoning capabilities (GPT 4o-mini, Panel C), and based on a combination of the three classifications above (Panel D), in which only events where all three aforementioned methods deliver the same classification are used. 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. 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

A Kalman Filter

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 1). 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;

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

and the objective is to maximize it with respect to the parameter vector of interest: $\theta = \begin{bmatrix} w_0 & \gamma & \phi & \rho \end{bmatrix}$.

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 1, 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.[24]

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 $\sigma^2_\tau = \frac{w_0}{[\Phi^{-1}(0.95)]^2 \times T}$, with $T = 732$ months (our sample length), $w_0 = 1$ as per our choice of an initial value for w_0, and Φ is the standard normal CDF.

[24] 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 a Simulated Annealing (SA) strategy. 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 simulated annealing. In short, the SA method entails searching over a set of candidate models to reach the best global solution. To implement the SA 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 1. This grid considers five different values, starting at a small variance of 0.01, up to $R \approx 0.16$ - which is the variance of the residual from the regression used to obtain the initial guess for the scaling parameter as discussed in the previous section.

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 — where it balances out the reliance on the measurement versus the state-space prediction based on the ratio of variances (Eq. (A.5)). We consider a wide grid of 24 points, $\sigma_\eta^2 \in \{0.25, 0.5, ..., v\} \times \sigma_\varepsilon^2$ with a fixed step size of 0.25 and $v = \frac{1}{R} \approx 6$, to explore an extensive set of possible solutions for the filter. Hence, interacting the grids, we run the entire filtering procedure for a total number of $5 \times 24 = 120$ different $(\sigma_\varepsilon^2, \sigma_\eta^2)$-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 annealing grid size unaltered.[25]

A.2.3 Optimization: Simulated Annealing

After setting up the annealing grid, we can start estimating the Kalman Filter for each of the $a = 1, ..., 120$ schemes - which can be interpreted as an *outer loop* over the filter architectures.

[25] 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.; $\sigma_\xi^2 = \frac{0.016^2}{(1-0.932\times0.96)^2} = 0.023$.

We also consider an *inner loop* for each filter a, to iteratively optimize the scaling factor β from the measurement equation. Precisely, within each annealing iteration, we perform at most $J = 50$ optimization rounds over the scaling factor. The procedure is as follows.

First, for some annealing scheme a, 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 parameters of interest:

$$\mathcal{S}^{a,1} = \{\hat{\beta}^{a,1}, \hat{\theta}^{a,1}\}, \quad \text{with} \quad \hat{\theta}^{a,1} = \begin{bmatrix} \hat{w_0}^{a,1} & \hat{\gamma}^{a,1} & \hat{\phi}^{a,1} & \hat{\rho}^{a,1} \end{bmatrix},$$

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

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

, where

$$\hat{w}_t^{a,1} = \hat{w_0}^{a,1} + \hat{\tau}_t^{a,1} + \hat{u}_t^{a,1}$$

, and

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

After this first iteration, we use the estimate for the scaling factor $\hat{\beta}^{a,1}$ 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 annealing scheme a — 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: $|\hat{\beta}^{a,j} - \hat{\beta}^{a,j-1}| < 10^{-3}$. When convergence is reached, we take the stabilized solution $\mathcal{S}^{a,\star}$, and extract the parameter estimates to construct the set of weights for annealing scheme a.

After completing the full estimation procedure, we will have obtained a total of $A = 120$ optimized solution sets;

$$\mathcal{S}^{\star} = \{\mathcal{S}^{1,\star}, ..., \mathcal{S}^{120,\star}\}.$$

The last step is to rank these solutions according to the value of 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 filter as a weighted combination of all the A candidates:

$$KF^{\star} = \sum_{a=1}^{A} \omega^{a} \, \mathcal{S}^{a,\star}, \tag{A.10}$$

where the weights ω^{a} are determined by the inverse ranks of the solutions, akin to the method described in Aiolfi and Timmermann (2006). Precisely, let r^{a} denote the rank of solution a, with $r^{a} = 1$ corresponding to the lowest NLL (best) and $r^{a} = A$ to the highest (worst). Then, the weights are defined as:

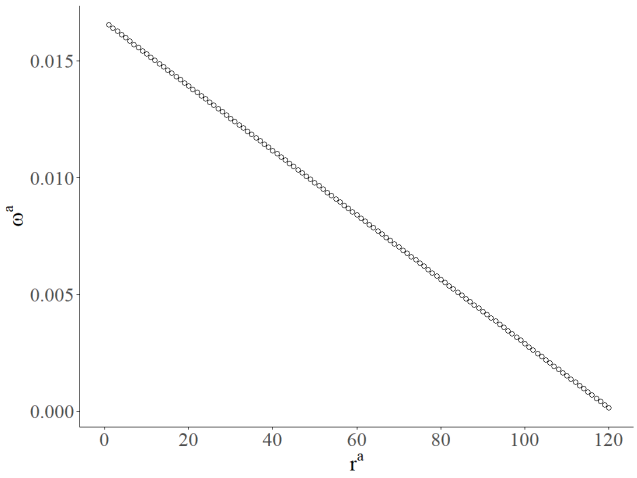
$$\omega^{a} = \frac{A - r^{a} + 1}{\mathcal{A}}. \tag{A.11}$$

, where $\mathcal{A} = \frac{A(A+1)}{2}$. In Figure A.1 we visualize Eq. (A.11) for our case of $A = 120$, 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. Hence, after all processing steps, $KF^{\star}$ represents the optimal rank-weighted solution of the Kalman Filter across the entire grid of possible solutions.

Figure A.1: Inverse Rank-Weighting, $A = 120$

This figure provides an illustration of the rank-weighting formula from Eq. (A.11), for $A = 120$ possible solutions. The total sum of the weights is equal to 1.



A.3 Standard Errors and P-Values

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 rank-weighted parameter estimates coming from the final Kalman Filtering solution (Eq. A.10);

$$KF^{\star} = \{\hat{\beta}, \hat{\theta}\}, \quad \text{with} \quad \hat{\theta} = \begin{bmatrix} \hat{w}_0 & \hat{\gamma} & \hat{\phi} & \hat{\rho} \end{bmatrix},$$

and use these to construct the empirical distributions 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 $\hat{w}_t^{RI}$, 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[26] 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:

[26] 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).

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

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 full annealing scheme described in Section A.2, producing a new set of parameter estimates:

$$\{\hat{\beta}^{(b)}, \hat{\theta}^{(b)}\}.$$

By bootstrapping over the full annealing 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 $(\sigma_\varepsilon^2, \sigma_\eta^2)$-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 $\beta = \beta^0$; $\theta = \theta^0 = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$[27] 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 out 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.

[27] 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 LLM Events

In Table B.1 we present the events file that we extracted from the reasoning GPT 4o-mini Large Language Model by OpenAI, using the API prompting functionality.

Table B.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.

C 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 distinction 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.

D Robustness: 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:

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

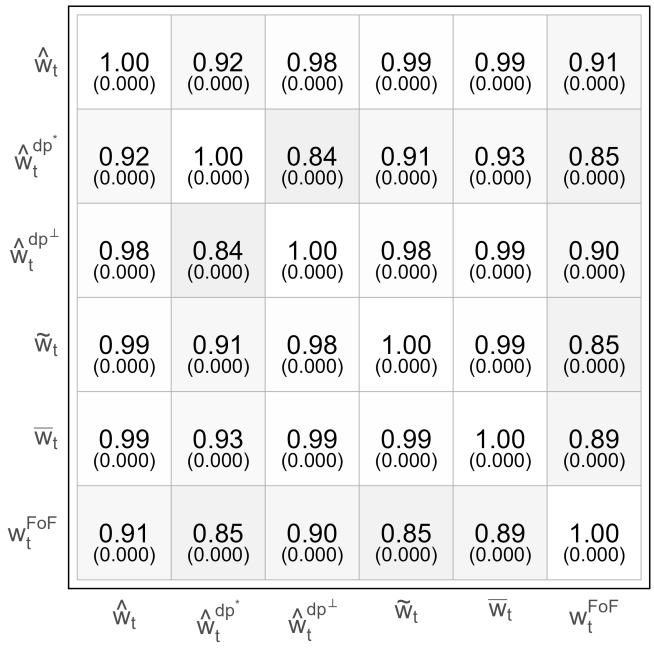
where d_1, d_2, d_3 are the averages of the dp-ratio computed from Jan 1927 - Dec 1954, Jan 1955 - Dec 1994, and Jan 1995 - Dec 2023, respectively. The Is are indicators equal to one for the corresponding period and are zero otherwise.

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. In the main text, we refer to this version of the dp-ratio as $dp_t^{\perp}$. Finally, 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 $\tilde{w}_t$.

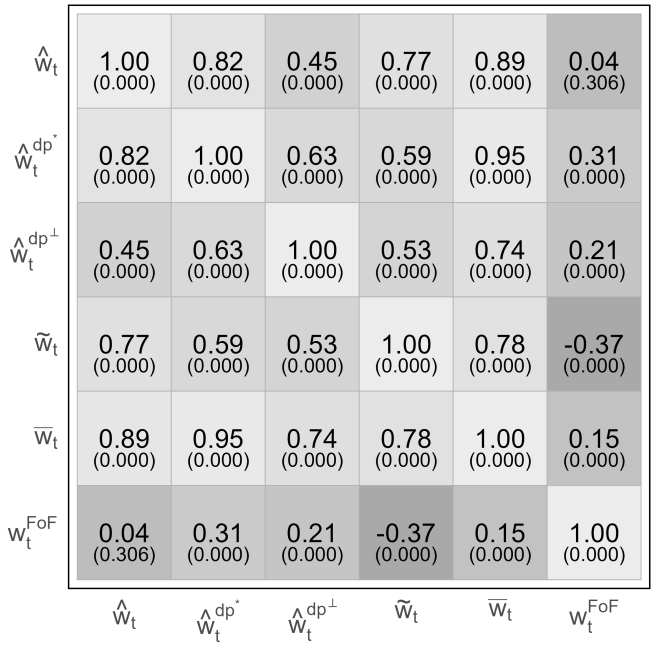
In total, this means that we obtain four sets for the filtered weights, obtained under different estimation regimes. As a simple benchmark, we create a simple ensemble of these series by averaging estimates within a month across models, and we label this as $\overline{w}_t$. Figure D.1 shows the raw as well as the detrended correlations between our estimated weights and to the ones based on the Flow-of-Funds data (w_t^{FoF}). Figure D.2 plots the time-series path of the estimated series. Finally, Table D.1 shows the parameter estimates associated to the different versions of the weights.

Figure D.1: Correlations Across Filtered Weights

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, $\hat{w}_t^{dp^*}$ and $\hat{w}_t^{dp^\perp}$ 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. $\overline{w}_t$ 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.



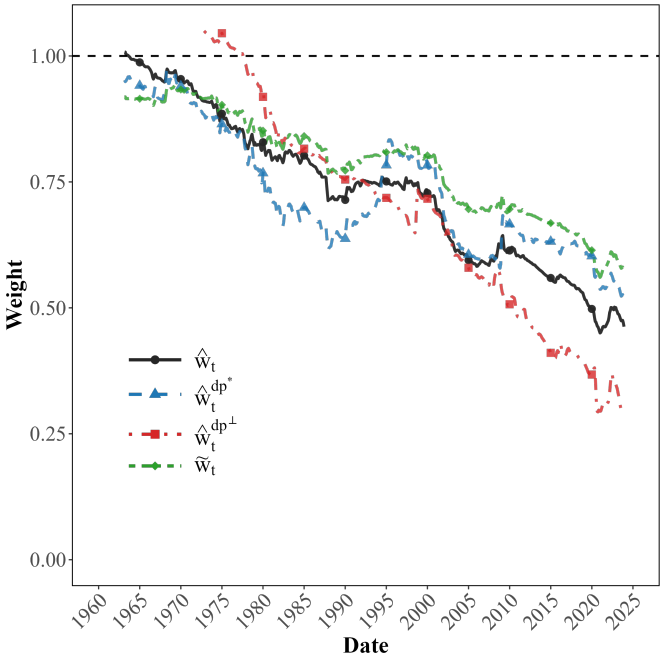
(A) Raw Series



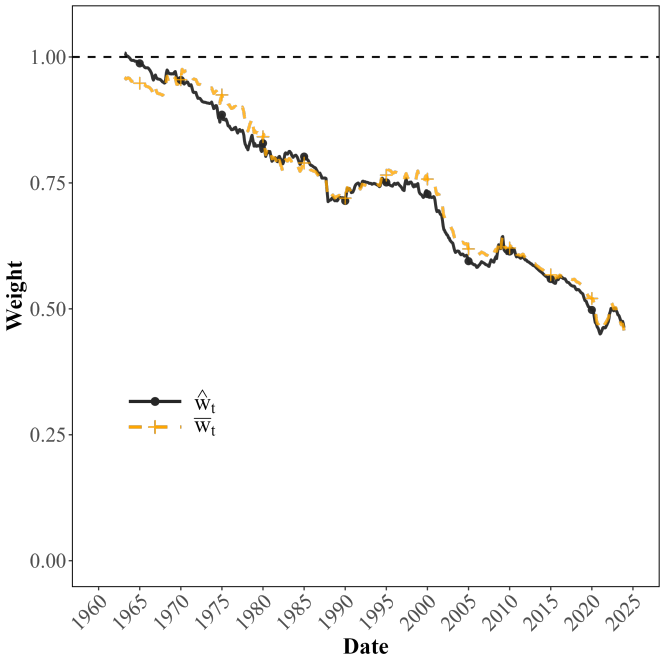
(B) Detrended Series

Figure D.2: Alternative Weight Estimates

This figure plots the 3-months rolling averages of our estimated weights over the period Jan 1963 to Dec 2023. $\hat{w}_t$ (black) is the filtered weight from our main analysis. As described in Appendix D, $\hat{w}_t^{dp^*}$ (blue) and $\hat{w}_t^{dp^\perp}$ (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. 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).



(A) Baseline and Alternative Weight Estimates



(B) Baseline and Alternative Weights Ensemble

Table D.1: Parameter Estimates Across Weight Variations

Version	w_0	γ	ϕ	ρ
	1.0032	-0.0007	0.3053	0.9573
$\hat{w}_t$	(0.950)	(0.002)	(0.000)	(0.000)
	(0.550)	(0.000)	(0.000)	(0.000)
	0.9579	-0.0006	0.3909	0.8595
$\hat{w}_t^{dp^*}$	(0.680)	(0.216)	(0.002)	(0.000)
	(0.350)	(0.104)	(0.002)	(0.000)
	1.0862	-0.0012	0.3220	0.9112
$\hat{w}_t^{dp^\perp}$	(0.518)	(0.016)	(0.020)	(0.000)
	(0.722)	(0.008)	(0.020)	(0.000)
	0.9131	-	0.3059	0.9575
$\tilde{w}_t$	(0.278)	(-)	(0.048)	(0.000)
	(0.272)	(-)	(0.048)	(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, $\hat{w}_t^{dp^*}$ and $\hat{w}_t^{dp^\perp}$ 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. 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 $w_0 = 1$, $\gamma = 0$, $\phi = 0$, $\rho = 0$. The one-sided p-values test the same, but against the alternative hypotheses that $w_0 < 1$, $\gamma < 0$, $\phi > 0$, $\rho > 0$.

E Robustness: Irrelevance of Institutions Simulation

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 household expectations being the only thing that matter 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:

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

, where we draw $\varepsilon_t^s \overset{\text{iid}}{\sim} \mathcal{N}(0, 0.05)$. Here, the value we choose for the variance of ε_t^s is arbitrary, and increasing it would lead mechanically to less informative signals coming from the measurement.

We repeat the entire Kalman Filtering strategy using dp_t^s as the measurement. The only thing we change in the initialization of the parameters compared to our original set-up is that we set the initial guess for w_0 (the intercept of the state-space equation for the weights) to 0.5, to make a completely unbiased guess of the influence of retail versus professional investors at the beginning of time.

The results are presented in Figure E.1, which confirms the capacity of our KF to recover even processes that are constant over time. The filtered series in gray reflects that informative updates coming from the dp-ratio pull the estimates toward the true state. The graph additionally shows the intercept is revised in the appropriate direction — towards 1 — relatively quickly after receiving information coming from the measurement. In Table E.1 we show the accompanying parameter estimates, which convey the same message: The KF is able to recover the scaling parameter, it revised the intercept correctly, and it recognizes that cyclical components and discount rates 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.

Figure E.1: Filtered States For Simulated Measurements

This figure shows the Kalman Filter 3-month rolling average of the estimates for the latent influence of retail investors on market valuations. Measurements are simulated according to Eq. E.1, such that the true states correspond to the dashed line drawn at a fixed level of 1.00.

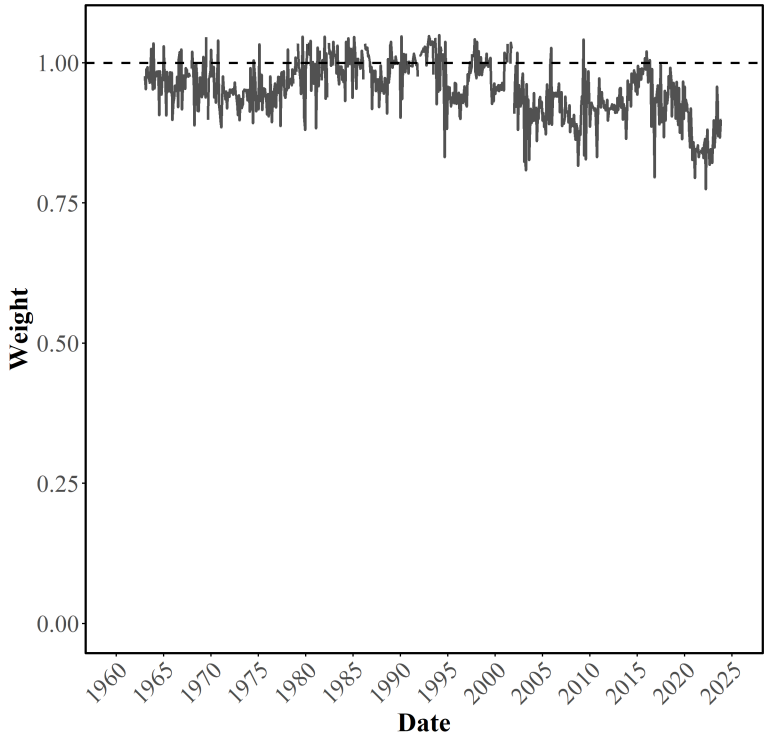


Table E.1: Parameter Estimates for Simulation Exercise

β	w_0	γ	ϕ	ρ
-1.0431	0.9762	-0.0001	0.0084	0.0065

This table shows the parameter estimates for the estimated weights shown in Figure E.1.