Asset Pricing with Dynamic and Static Investors

ABSTRACT

A central assumption in asset pricing theories is dynamic portfolio choice by agents. This assumption is violated when investors adopt static asset allocation strategies. The paper presents a tractable model with dynamic investors, whose asset allocation responds to news, alongside static investors, with constant asset allocation regardless of changing investment opportunities. The model uncovers the "*asset classification effect*," the effect of static asset allocation strategies on the prices of securities classified within target asset classes. Given fundamentals and discount rates, static asset allocation strategies raise stock prices and contribute to excess volatility, particularly when expected returns are low and volatile.

JEL classification: G11, G12, G14, G23.

Keywords: Asset pricing, asset allocation, portfolio constraints.

1 Introduction

The standard approach in financial economics postulates that asset prices are determined by agents who continuously optimize their asset allocation. For instance, in Merton (1973), asset prices are driven by the portfolio choice of a representative investor who dynamically adjusts the allocation of wealth across asset classes in response to changes in the investment opportunity set. In practice, however, the majority of investors make no change to their asset allocation over time (Ameriks and Zeldes, 2011).

This paper presents a theory of asset prices motivated by the observation that a large group of investors adopt a static asset allocation strategy. Those investors establish an asset allocation and maintain it over their desired horizon, regardless of the changes in the investment opportunity set that occur over time. Such static asset allocation strategies are commonly recommended by professional advisers, who might suggest, for example, that a conservative investor hold a 30/70 stocks/bonds portfolio, while a balanced investor hold a 60/40 stocks/bonds portfolio.

By focusing on the dynamic optimization of agents, the standard approach to asset pricing leaves no role for important considerations, such as whether static asset allocation strategies influence asset prices, and under what conditions this effect might be most pronounced. To fill this gap, this paper presents a tractable model in which asset prices result from the interaction of investors using heterogeneous asset allocation strategies.

The model introduces the notion of "*asset classification effect*," the effect of static asset allocation strategies on the prices of securities classified within target asset classes. This notion suggests that the aggregate value of assets within an asset class is at least as great as the wealth invested in that asset class to implement static asset allocation strategies. This principle holds true regardless of the expected cash flows generated by the assets and the discount rates required by the market participants. To the best of my knowledge, this finding has not been previously articulated in the literature, despite its simplicity. Although this effect is likely to be of broader importance, the analysis of the paper is centered around the equity asset class.

The "*asset classification effect*" offers a generalization of the "*index inclusion effect*," a phenomenon where the inclusion of stocks into an index increases their prices. The general idea is fairly simple: just as stocks included in a benchmark index attract the capital of index trackers, the classification of a security within an asset class draws the investment from static asset allocation strategies. In both cases, the demand for securities unrelated to their future fundamentals drives asset prices above discounted cash flows.

The model considers two asset classes: one generating a risk-free return, and the other consisting of securities that distribute risky dividends. There are two groups of agents, who differ in their asset allocation strategy – dynamic investors, and static investors. Dynamic investors optimally revise their asset allocation upon the arrival of information to the market. Static investors hold a constant allocation between the two asset classes, regardless of how the risk and expected returns of these asset classes change over time. Except for heterogeneous asset allocation strategies, the model has a standard structure.

Thanks to its tractability, the model extends to the cross-section of risky assets, allowing for an analysis of the relationship between the well-documented index inclusion effect and the asset classification effect introduced in this paper. The index inclusion effect stems from investors constrained from stock picking, who affect relative prices in the cross-section of stocks. In contrast, the asset classification effect stems from investors constrained from market timing, who affect the relative prices of stocks and bonds.

The asset classification effect can be demonstrated through the analysis of a change in the investment opportunity set, facilitated by the exact closed-form solutions of the model. As market volatility or the risk-free interest rate rise, dynamic investors reduce their allocation of wealth to the risky asset class, driving down the price of risky assets. Meanwhile, static investors maintain a constant proportion of their wealth allocated to the risky asset class, thereby cushioning the price of securities it comprises.

Through time, static investors enforce investment decisions that are not responsive to news about the economic fundamentals, generating cash-in-the market features that affect the level of asset prices. This effect becomes relatively more important when the expected excess returns on risky assets are low and volatile.

Formally, static asset allocation strategies give rise to a rational asset price bubble. Rational asset price bubbles are considered incompatible with the dynamic optimizing behavior of economic agents (Tirole, 1982), absent portfolio constraints (Hugonnier, 2012). As shown in this paper, a rational asset price bubble arises when some of the agents depart from dynamic maximization by adopting a static asset allocation strategy. This strategy introduces a divergence between the present discounted value of the fundamentals and the level of asset prices consistent with rational expectations.

Moreover, static asset allocation strategies contain information about the response of investors to price changes. Market movements that grow the wealth of static investors prompt the reinvestment of capital gains in fixed proportions across asset classes. The paper finds that this procyclical price pressure gives rise to conditional price volatility in excess of the volatility of fundamentals, but still connected to it.

Generally speaking, traditional approaches to asset pricing assume that agents optimize their portfolio choice dynamically. This assumption is common in frameworks where the agent is a household optimizing consumption (Merton, 1973), a firm optimizing production (Cochrane, 1991), and a specialized intermediary facing capital constraints (He and Krishnamurthy, 2013) or investment mandates (Koijen and Yogo, 2019).

It is somewhat surprising that despite the widespread adoption of the static asset allocation strategy, theoretical exploration of its impact on asset prices remains limited. Related work by Chien, Cole, and Lustig (2011) shows that heterogeneous asset allocation strategies help to match asset prices and the distribution of household wealth. In their model, agents trade state-contingent bonds with finite maturity, which rule out rational bubble considerations that are central to this paper. Gabaix and Koijen (2022) point out that wealth flows into static asset allocation investment funds drive asset price fluctuations. This effect arises from the absence of unconstrained agents, integral to this paper. This paper emphasizes the intertemporal consistency of static asset allocation strategies, which makes it rational for unconstrained investors not to expect the realignment of prices with discounted fundamentals. The contribution of this paper is to introduce the asset classification effect, which, to my knowledge, is new to the literature.

The effect of demand forces on asset prices has been explored, in relation to stock indexes, in a program of research pioneered by Harris and Gurel (1986) and Shleifer (1986). More recently, Basak and Pavlova (2013) show that the incentive of professional investors to outperform their benchmark generates procyclical leverage decisions, leading to a higher index level and volatility. Related literature on passive investing includes Greenwood and Sammon (2025), Pavlova and Sikorskaya (2023), and Haddad, Huebner, and Loualiche (2021). Building on this literature, this paper examines the distinct portfolio constraint imposed by static asset allocation strategies. Fully analytical solutions show that the resulting asset classification effect constitutes a generalization of the index inclusion effect, of importance even for the pricing of stocks outside benchmark indices.

The paper also relates to the literature on asset pricing with heterogeneous agents, a strand of which focuses on newswatchers and trend followers (Hong and Stein, 1999; Barberis and Shleifer, 2003). Although newswatchers resemble dynamic investors, trend followers differ sharply with static investors, who allocate wealth to stocks even when bonds are more efficient. Moreover, the paper builds upon the literature on intertemporal asset pricing, including Veronesi (1999), Basak and Chabakauri (2010), and Chabakauri (2013), which provides tractable characterizations of equilibria with stochastic investment opportunities primarily in models where agents engage in dynamic optimization.

The paper is organized as follows. Section 2 presents the model in the time series, and Section 3 generalizes it to the cross section of stocks. Section 4 explores selected extensions. Section 5 tests the predictions of the model. Section 6 concludes.

2 The Model

The model is set in continuous time over an infinite horizon and considers financial markets with two groups of agents, dynamic and static investors. Dynamic investors optimally revise their asset allocation in response to news. Static investors maintain a constant asset allocation, without regard to the revelation of information.

2.1 Assets

There are two classes of investment assets: a riskless investment and a risky investment. The riskless asset is elastically supplied and yields the instantaneous real rate of return r. The risky asset is an aggregate of individual equities, and distributes stochastic dividends based on the aggregate earnings of the firms in the economy. P_t denotes the ex-dividend price of the risky asset, and μ_t and σ_t represent the instantaneous price drift and diffusion, respectively. The aggregate earnings in the economy, denoted by E_t and expressed in real terms, follow a stochastic differential equation with drift m and diffusion ω,

$$dE_t = mdt + \omega dB_t, \tag{1}$$

where B_t is a Brownian motion that generates the filtration $\{\mathscr{F}_t\}$. This arithmetic process is motivated by the linear growth of real earnings. The earnings payout ratio is constant, so that the aggregate dividend per share, D_t, is a fixed proportion a of the earnings.[1]

2.2 Dynamic Investors

Dynamic investors optimize the utility function $U(c_t) = -e^{-\delta t - \gamma c}$, where c denotes consumption, and δ and γ are respectively patience and risk aversion parameters. Their portfolio choice responds to news about earnings, in the style of Merton (1973), and changes continuously as news reach the market.[2]

[1] Rights issues influencing the value of shares without affecting their supply to the public can account for negative dividends.
[2] Chien, Cole, and Lustig (2012) examine the effects of dynamic but intermittent portfolio rebalancing on asset prices.

Dynamic investors control their consumption and investment policies to maximize their expected intertemporal utility over an infinite time horizon, while respecting their budget constraint and transversality condition. The wealth of dynamic investors is denoted by W_t, and their derived utility from wealth is

$$J \equiv \max_{\{c,X\}} \quad \mathbb{E}_t\left[\int_t^\infty U(c_s)\ ds\right], \tag{2}$$

$$\text{s.t.} \quad dW = (rW - c)dt + XdY, \qquad \lim_{h\to\infty} \mathbb{E}\left[J_{t+h}\right] = 0. \tag{3}$$

In the above, $dY = (D - rP)dt + dP$ is the return of a share of the risky asset financed at the risk-free rate, and X_t is the number of such shares held by dynamic investors. This optimization program is similar to that in Veronesi (1999) and others, with the key distinction that in this paper dynamic investors interact with other participants in the market who follow static asset allocation strategies, as detailed below.

2.3 Static Investors

Static investors allocate their wealth in a fixed proportion across asset classes, without regard to the going and prospective market prices. To implement this approach, which could be microfounded by a preference for avoiding continuous market observation, a group of agents transfers their wealth into professional investment funds that follow static asset allocation strategies. Investment funds thus experience idiosyncratic wealth flows, and continuously rebalance their portfolios to maintain target exposures across asset classes. Investment funds are, without any loss of generality, aggregated into a representative fund whose wealth, V_t, is allocated in a constant proportion, θ, to the risky asset class.[3]

Static investors collectively hold Q_t shares of the risky asset class, where

$$Q_t = \theta V_t / P_t. \tag{4}$$

Static investors present a downward sloping demand for the risky asset class, remindful of Harris and Gurel (1986) and Shleifer (1986). For simplicity, it is assumed that static

[3] For example, a fund with wealth $V_x = 100\$$ and equity allocation $\theta_x = 0.5$ and a fund with wealth $V_y = 200\$$ and $\theta_y = 0.75$ aggregate into a representative fund with wealth $V = 300\$$ that allocates to equities the average of the allocation of the two agents weighted on their wealth, $\theta = 0.67$. The subsequent wealth flows into each of the funds are scaled equivalently.

investors reinvest the dividends distributed by risky assets. Their wealth dynamics are

$$dV = V\big[(1-\theta)rdt + \theta(dP + Ddt)/P\big] + \pi dF \tag{5}$$

where F is a Brownian motion under the risk-adjusted measure adapted to $\{\mathscr{F}_t\}$ which describes wealth flows to the static allocation fund net of share redemptions, and π is a loading parameter. The flows process F summarizes the decisions of economic agents to invest in or divest from the static fund. The wealth flows are considered uncorrelated with economic fundamentals until Section 4, where this assumption is relaxed.

Equation (5) is a special case of Equation (3) when portfolio shares are constrained by the asset allocation strategy θ and the investor's wealth is subject to flow risk πdF.[4] The wealth of static investors, V, rises in past stock returns dP/P, all else equal. Section 4.2 shows that Equation (5) contributes to the predictable amplification of price volatility.

2.4 Market Clearing

The shares of the risky asset are in fixed supply, $\overline{S}$, normalized to one without loss of generality.[5] The market clearing condition is

$$X_t(P, D, V) + Q_t(P, V) = \overline{S}. \tag{6}$$

2.5 Equilibrium

The equilibrium consists of a price, P, of the risky asset such that the supply of shares, $\overline{S}$, is equal to their demand, $X+Q$. The portfolio choice of dynamic investors maximizes their indirect utility from consumption, given their wealth, corporate earnings, and market prices. Given the wealth flows, static investors allocate a fixed share θ of their wealth to the risky asset. The equilibrium is described by the following conditions.

$$X + Q = \overline{S}, \qquad 0 = \max_{\{c,X\}} U(c) + \frac{\mathbb{E}_t[dJ(W,V)]}{dt}, \qquad Q = \theta V/P.$$

The first equation is the market clearing condition, the second one the Bellman equation of the dynamic investors, and the third one the asset allocation strategy of static investors. The equilibrium is Walrasian and every share trades at the going market price.

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[4] Following extreme fund outflows, V could turn implausibly negative. Its dynamics near this barrier can be regulated by a term ηdL, where η is the speed of reflection and L the local time of V at zero, without affecting the content of the results.

[5] In standard models with stochastic supply, unlike in this paper, assets become worthless when holding them is not optimal.

First, consider the price of the risky asset class in the absence of static investors. Throughout, let $\mathbb{E}_t^*$ denote the expectation taken with respect to the probability measure adjusted for the dynamic investors' preferences toward risk.

Lemma 1. Equilibrium without Static Investors.

$$P_t = \underbrace{\mathbb{E}_t^* \left[\int_t^\infty e^{-r(s-t)} D_s \, ds \right]}_{Fundamentals}.$$

Proof. Special case of Proposition 1. See also Veronesi (1999).

By replacing the earnings process into Lemma 1, the price obtains in closed form,

$$P_t = p_g + p_D D_t + p_m m, \tag{7}$$

where the parameters governing the price level are $p_g = -\frac{\gamma\omega^2}{r^2}$, $p_D = \frac{1}{r}$, and $p_m = \frac{1}{r^2}$.[6]

Lemma 1 presents a standard dividend discount valuation model, which can also be derived by iterating forward the condition $P_t = \mathbb{E}_t^*[e^{-rdt}(P_{t+dt} + D_t)]$ and assuming the absence of "*rational bubbles.*" Rational bubbles are terms that affect both the current level of the asset price and its discounted future value equally. They are usually assumed away by imposing the transversality condition $\lim_{\Delta t \to \infty} \mathbb{E}_t^*[e^{-r\Delta t} P_{t+\Delta t}] = 0$. The reasoning is that, absent this condition, the asset price would exceed the discounted dividend stream. Agents would find it optimal to sell the risky asset short and invest at the risk-free rate to replicate the dividend stream, until the equivalence is restored. For this reason, bubbles disappear when agents adopt a dynamic maximizing behavior (Tirole, 1982).

Proposition 1 below demonstrates that the pesence of static investors generates a rational bubble, $\theta V_t = \mathbb{E}_t^*\left[e^{-rdt}\theta V_{t+dt}\right]$. This is because, regardless of fundamentals and discount rates, static investors exert price pressure on securities in the risky asset class. Moreover, as their asset allocation is static, it is rational to expect such price pressure to persist in the future. In risk-adjusted expectations, the demand of static investors for the risky asset class grows at the risk-free rate. These features imply that the equity exposure of static investors affects both the current level of the risky asset class price and its discounted future value equally. In the presence of a rational bubble, the high price of the risky asset class relative to its fundamental value is merited, as the expected total returns are equal to the returns on alternative assets (Stiglitz, 1990).

[6] To ease notation, the dividend payout ratio a is set to 1. The general case achieves by multiplying p_g, p_D, and p_m by a.

Proposition 1. Equilibrium with Dynamic and Static Investors.

$$P_t = \underbrace{\mathbb{E}_t^*\left[\int_t^\infty e^{-r(s-t)} D_s \, ds\right]}_{Fundamentals} + \underbrace{\mathbb{E}_t^*\left[e^{-rdt}\theta V_{t+dt}\right]}_{Asset\ Classification\ Effect}.$$

Proof. See Appendix A, which also reports the portfolio choice and consumption level that maximize the Hamilton-Jacobi-Bellman Equation for dynamic investors.

Proposition 1 outlines the first main result of the paper. It shows that, beyond the expected cash flow and the discount rates of marginal agents, the price of the risky asset class reflects the equity exposure of static investors. As this price represents the sum of all stock prices, the proposition highlights the presence of an "*asset classification effect.*" This effect suggests that the aggregate value of assets within an asset class is at least as great as the wealth invested in that asset class to implement static asset allocation strategies. Section 3 carves out which stocks in the cross-section are most impacted by this effect.

The asset classification effect can be illustrated through a change in the investment opportunity set. As the opportunity cost of the risky asset class temporarily increases, its aggregate value declines under the selling pressure of dynamic investors reallocating their portfolios toward the risk-free asset. However, static investors, who hold a constant asset allocation over time, maintain their exposure to the risky asset class unchanged. Through this mechanism, the demand pressure of static investors provides a floor to the aggregate value of the securities in the risky asset class.

It is important to emphasize that this mechanism is not specific to the CARA utility of dynamic investors, whose main advantage is tractability; it also extends to cases where dynamic investors have CRRA and more general utility functions. The fundamental condition for the asset classification effect is that some investors engage in dynamic intertemporal optimization, while others follow a static asset allocation strategy.

For instance, as $r \to \infty$, the dividend stream becomes worthless, prompting dynamic investors to allocate their entire wealth to the bond market and set $X = 0$. In models with dynamic optimization, risky assets would be worthless. In this model, static investors would maintain their exposure to the risky asset class unchanged. Market clearing ensures $P = \theta V$, making stock prices a mere unit of account for the *cash-in-the-market.* Naturally, some agents may adjust their exposure to static asset allocation investment strategies in response to news. Section 4.1 shows that the results remain robust to this consideration.

One more insight emerging from the proposition is that the price of risky assets is influenced by the *stock* of wealth of static investors, rather than solely by stochastic wealth *flows*. The effect of wealth flows on the price of risky assets has received the attention of an active area of literature (for instance, Coval and Stafford, 2007). Proposition 1 shows that the equilibrium level of asset prices reflects the stock of wealth of static investors, which incorporates flows, but is more broadly influenced by the returns on both risk-free and risky assets, and follows the intertemporal dynamics of Equation (5).

From Proposition 1, the total value of the risky asset class obtains in closed form as

$$P_t = \mathrm{PDV}_t(D) + \theta V_t, \tag{8}$$

where $\mathrm{PDV}_t(D) = p_\gamma + p_D D_t + p_m m$ denotes the discounted value of the expected aggregate dividend stream, which incorporates the risk adjustment $p_\gamma = -\frac{\gamma}{r^2}\left(\frac{\omega}{r}+\theta\pi\right)^2$ required by dynamic investors for the exposure of the price to earnings risk and flow risk. The workings of dynamic investors ensure that the price corresponds to Equation (8). On the other hand, the intertemporally consistent price pressure of static investors generates the rational asset price bubble.[7] In this regard, the price impact of trades is tied to the dynamic behavior of the investors. The equity exposure of static investors, θV, affects the price of the risky asset regardless of the cash flows, D, the risk-free rate, r, and the adjustment for risk, p_γ, required by dynamic investors who are marginal to asset prices.

Quantities held by investors characterize the equilibrium in conjunction with the price.

$$X(P, D, V) = \frac{\mu - rP + D}{r\gamma\sigma^2} - \frac{1-\theta}{r\gamma}Q, \qquad Q(P, V) = \theta V/P. \tag{9}$$

Dynamic investors hold a position in the risky asset class, X, that increases with expected returns per unit of variance and decreases with the risk-free rate. Equilibrium prices may change under the pressure of static investors, even if the discount rate or the fundamentals have not, motivating the hedging term of the demand of dynamic investors. Static investors holds a position, Q, that consistently fulfills their strategy. The market clearing condition, $X + Q = 1$, together with Equation (8) and the asset allocation strategy of static investors, implies that the equilibrium holdings can be characterized as follows.

$$X_t(P, D, V) = \mathrm{PDV}_t(D)/P, \qquad Q_t(P, V) = \theta V/P. \tag{10}$$

[7] Section 4.1 shows that the rational price bubble also depends on the correlation between wealth flows and earnings news.

Ceteris paribus, as the present discounted value of fundamentals rises, so does the proportion of the risky asset class held by dynamic investors. Conversely, the proportion of the risky asset class held by static investors rises in bad times.

The asset classification effect is more pronounced when the expected returns on the risky asset class are low and volatile. All else equal, when the risk-return ratio is higher the scope for static investors' demand to affect asset prices is more limited, as dynamic investors take comparatively more aggressive positions. By contrast, when dynamic investors reduce their exposure to the risky asset class, the effect of static investors' demand on asset prices is relatively more important.

Corollary 1. The forecast accuracy of the price of the risky asset class for the aggregate stream of dividends rises in the expected return to risk ratio of the risky asset class.

Proof. Under the earnings process of Equation (1), $\mathrm{PDV}_t(D)$ is the best linear unbiased estimator of the dividend stream. Equation (10) shows that $P_t = \mathrm{PDV}_t(D)$ when $X_t = 1$, making the price an accurate forecast. In general, the forecast accuracy of stock prices for dividends rises when dynamic investors have stronger incentives to allocate resources to the risky asset class, which occurs as the expected return to risk ratio rises. Q.E.D.

Corollary 1 highlights a connection between price forecast accuracy, portfolio holdings, and the investment opportunity set. For stock prices to accurately reflect future dividends, it is essential that dynamic investors find it attractive to allocate resources to the risky asset class.[8]

Overall, this section has demonstrated the presence of an asset classification effect, whereby the sum of the total market value of stocks is at least as great as the equity exposure of investors following static asset allocation strategies. In the time series, the asset classification effect becomes more important as the expected excess returns from holding risky assets are low and volatile.

3 The Cross Section

The model presented thus far characterizes the aggregate stock market in the time series. Which stocks appreciate the most, when the wealth of static investors rises?

To model the cross section of stocks, *three agents* are required. Dynamic investors engage in stock picking and market timing. Static investors can be grouped into stock

[8] The effort to connect price forecast accuracy to observable market conditions shares similarities with Dávila and Parlatore (2023), who study the relation between price informativeness and idiosyncratic volatility in a heterogeneous beliefs model.

pickers, who select stocks optimally but do not time the market; and index trackers, constrained from both stock picking and market timing. Figure 1 illustrates the agents.

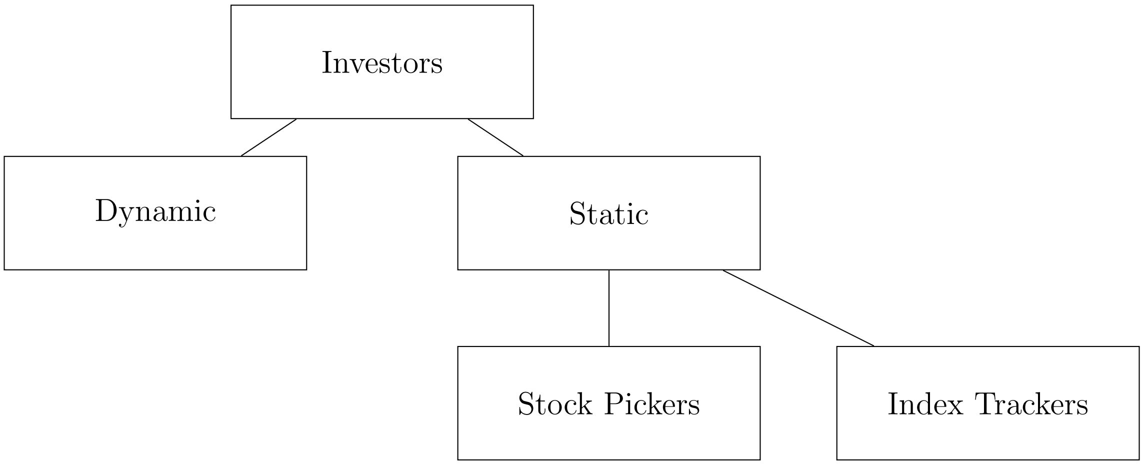

FIGURE 1: **Agents**. The figure illustrates the agents based on their portfolio constraints. Dynamic investors are unconstrained in the time series and in the cross section of stocks. Static investors hold constant equity shares over time. Within the cross section, static asset allocation stock pickers actively select stocks to optimize their portfolios, while static asset allocation index trackers passively replicate the performance of a benchmark index.

3.1 Assets

There are I firms in the economy. Real earnings E_{it} of firm i at time t follow the dynamics

$$dE_{it} = m_i dt + \omega_i dB_{it}, \tag{11}$$

where m_i denotes the expected growth of earnings and ω_i their volatility. B_{it} is a Brownian motion. The pairwise correlations between earnings news are $dB_{it}dB_{jt} = \omega_{ij}dt$. Firms' stock shares trade at the real price P_{it} and distribute dividends D_{it} with constant earnings payout ratio a. μ_{it} and σ_{it} denote the price drift and diffusion of stock i, and σ_{ijt} the price correlation between stocks i and j. The shares of each stock are in fixed supply, $\overline{S}_i$, normalized to one without loss of generality.

The price of the risky asset class of Section 2 is the total market value of equities,

$$P_t = \sum_{i=1}^{I} P_{it}.$$

There is a stock market index consisting of a collection of $N < I$ stocks. As the supply of shares is fixed, float-adjusted market capitalization index weights coincide with price index weights. The index level is

$$P_t^{\mathrm{IDX}} = \sum_{i=1}^{I} N_i P_{it},$$

where the dummy variable N_i equals 1 if stock i is included in the index and 0 otherwise. Consistently with the previous section, real aggregate earnings in the economy continue to follow Equation (1), defining $m = \sum_{i=1}^{I} m_i$ and $\omega = \sqrt{\sum_i \omega_i^2 + \sum_i \sum_{j \neq i} \omega_{ij}}$.

3.2 Dynamic Investors

The wealth of dynamic investors follows classical Merton (1973) dynamics

$$dW_t = (rW_t - c_t)dt + \sum_{i=1}^{I} X_{it}[(D_{it} - rP_{it})dt + dP_{it}] \tag{12}$$

Their utility function and transversality condition are in Section 2.2. Dynamic investors optimally select the number of shares, X_{it}, in the cross section of stocks. The aggregate number of shares of risky assets held by dynamic investors is $X_t = \sum_i X_{it}$. As previously derived, the proportion of their wealth allocated to the risky asset class equals $X_t P_t / W_t$.

3.3 Static Investors

As a group, static investors allocate a proportion θ of their wealth in the stock market, with important differences in the cross section. Static "*stock pickers*" actively optimize their portfolio in the cross section of stocks. Static "*index trackers*" passively buy each stock in proportion to its index weight. The wealth of static investors discussed previously is the sum of the wealth of static stock pickers and index trackers, $V_t = V_t^A + V_t^{\mathrm{IDX}}$.

3.3.1 Stock Pickers

Static asset allocation stock pickers have wealth V^A, allocated in fixed proportion θ to the stock market, and receive a share π^A of wealth flows F. In the cross section, they invest in each stock in proportion q_{it}. Their wealth follows the dynamics

$$dV_t^A = rV_t^A(1-\theta)dt + \theta V_t^A \sum_{i=1}^{I} q_{it}\ (dP_{it} + D_{it}dt)/P_{it} + \pi^A dF_t. \tag{13}$$

Static asset allocation stock pickers actively select their cross-sectional stock holdings, q_{it}, as a solution to their mean-variance portfolio optimization problem,

$$\max_{\{q_{it}\}} \ \mathbb{E}_t[dV_t^A] - 0.5\gamma\mathbb{E}_t[(dV_t^A)^2] \quad \text{s.t.} \quad \sum_{i=1}^{I} q_{it} = 1, \qquad \theta \text{ given.} \tag{14}$$

In the above, the risk aversion γ of stock pickers equals that of dynamic investors.[9] Effectively, asset allocation stock pickers differ from dynamic investors only because the proportion of their wealth invested in stocks is fixed, rather than sensitive to changes in the investment opportunity set. Let $\{\hat{q}_{it}\}$ denote the solution to the portfolio optimization problem problem in Equation (14). The number of shares of the i-th stock optimally held by static asset allocation stock pickers is $Q_{it}^A = \hat{q}_{it}\theta V_t^A/P_{it}$.

3.3.2 Index Trackers

Static asset allocation index trackers have wealth V^{IDX}, allocated in fixed proportion θ to the stock market, and receive a share $\pi^{IDX} = \pi - \pi^A$ of wealth flows F. They passively invest a fraction of their equity allocation into each stock equal to its weight in the index. Thus, their cross-sectional stock holdings are represented by the dummy variable $\lambda_i = N_i/N$, and their wealth dynamics follow

$$dV_t^{\text{IDX}} = rV_t^{\text{IDX}}(1-\theta)dt + \theta V_t^{\text{IDX}} \sum_{i=1}^{I} \lambda_i\ (dP_{it} + D_{it}dt)/P_{it} + \pi^{\text{IDX}} dF_t. \tag{15}$$

The number of shares of the i-th stock held by static asset allocation index trackers is $Q_{it}^{\text{IDX}} = \lambda_i\theta V_t^{\text{IDX}}/P_{it}$.

[9] This assumption does not affect the results, and is meant to create a level-playing field with the preferences of dynamic investors, ensuring that the financial decisions of asset allocation stock pickers are not driven by their risk preferences.

3.4 Market Clearing

The market clearing condition for the i-th stock is

$$\underset{\substack{\downarrow \\ X_{it}}}{\text{Dynamic Investors}} + \underset{\substack{\downarrow \\ Q^{A}_{it}}}{\text{Stock Pickers}} + \underset{\substack{\downarrow \\ Q^{\text{IDX}}_{it}}}{\text{Index Trackers}} = \overline{S}_i. \tag{16}$$

Proposition 2. Equilibrium in the Cross Section of Stocks.

$$P_{it} = \underbrace{\mathbb{E}^*_t\left[\int_t^{\infty} e^{-r(s-t)} D_{is}\, ds\right]}_{Fundamentals} + \overbrace{\hat{q}_{it}\mathbb{E}^*_t\left[e^{-rdt}\theta V^A_{t+dt}\right] + \underbrace{\lambda_i \mathbb{E}^*_t\left[e^{-rdt}\theta V^{IDX}_{t+dt}\right]}_{Index\ Inclusion\ Effect}}^{Asset\ Classification\ Effect}.$$

Proof. See Appendix B, which also reports the portfolio choice and consumption level maximizing the Hamilton-Jacobi-Bellman equation of dynamic investors and the optimal portfolio choice of stock pickers.

Proposition 2 outlines the second main result of the paper. It shows that each stock's price reflects its discounted future fundamentals, along with the price pressure from the investors following a static asset allocation strategy, including both active stock pickers and passive index trackers.

As the proposition illustrates, the "*asset classification effect*" offers a generalization of the "*index inclusion effect.*" Both effects stem from investors' portfolio constraints. The index inclusion effect arises from the cross-sectional index tracking constraint, λ_i, which prevents stock selection. The asset classification effect arises from the intertemporally static asset allocation strategy, θ, which prevents market timing.

Proposition 2 shows that, just as stocks included in an index can become overpriced relative to their fundamentals due to the price pressure from index trackers, securities classified within an asset class can become overpriced due to the price pressure from static asset allocation strategies.

In contrast to the index inclusion effect, which pertain to the relative pricing of stocks included and not included into a benchmark index, the asset classification effect pertains to the relative pricing of the risky asset class and the risk-free asset. This is because the asset classification effect relates to the wealth that is allocated to the stock market without consideration of intertemporal changes in its opportunity cost.

Appendix B shows that the i-th stock price can be expressed in closed form as

$$P_{it} = \mathrm{PDV}_{it}(D_{it}) + \theta\big[\hat{q}_{it}V_t^A + \lambda_i V_t^{\mathrm{IDX}}\big], \tag{17}$$

where $\mathrm{PDV}_{it}(D_{it}) = p_{\gamma_i} + p_D D_{it} + p_m m_i$ is the present discounted value of dividends distributed by stock i and incorporates the risk correction, $p_{\gamma_i} = -\frac{\gamma}{r^2}\big(\omega_i + \sum \omega_{ij}\big)$. The index inclusion dummy variable λ_i equals $1/N$ if the stock is included in the index and 0 otherwise. The price of index stocks rises in the equity exposure of index trackers, $\theta V_t^{\mathrm{IDX}}$, capturing a time varying benchmarking intensity.

A key insight from the proposition is that even active investors, such as stock pickers, exert price pressure on stocks as long as they adhere to static asset allocation strategies. Stock pickers following a static asset allocation strategy maintain a fixed share of their wealth, θV_t^{A}, in the equity asset class. Their optimal investment choice, $\hat{q}_{it}$, places more weight on the stocks with high expected return-to-risk ratio.

Importantly, $\hat{q}_{it}$ does *not* respond to changes in the risk-free rate, as the risk-free asset is not part of the stock picking problem given the fixed allocation of wealth to equity. Thus, while stock pickers select the most efficient stocks, they exert price pressure on the aggregate valuation of the risky asset class. This contrasts with dynamic investors, who time their allocation to the risky and risk-free asset classes.

Appendix B presents closed form solutions for $\hat{q}_{it}$, alongside the stock price drifts, volatilities, and pairwise correlations. Interestingly, the wealth of static investors influence correlations in excess of the fundamentals between pairs of stocks included in the index, a classical result, as well as between non-index stocks and both index and non-index stocks.

Overall, this section has demonstrated that the asset classification effect represents a generalization of the index inclusion effect, of importance even for stocks not included into any index. In the cross-section, the asset classification effect is more pronounced for i) index stocks, which attract the investment of index trackers, and ii) stocks with high and stable expected excess returns, which attract the investment of stock pickers.

4 Extensions

This section develops the baseline model of Section 2 in three key directions. Section 4.1 shows the robustness of the asset classification effect to the correlation between wealth flows and earnings news. Section 4.2 examines the implications of this effect for asset price dynamics. Section 4.3 discusses the asset classification effect in the Treasury market.

4.1 Wealth Flows and Earnings News

Thus far, wealth flows F were assumed to be uncorrelated with earnings news B. However, wealth invested under static allocation strategies may partly reflect information, and can be regarded as endogenous to the economy. To extend the model in this direction, let

$$dF_t = \rho dB + \sqrt{1-\rho^2} dZ_t, \tag{18}$$

where Z is a Brownian motion uncorrelated with earnings news. It appears reasonable to consider $0 < \rho < 1$, since some attentive fund shareholders may use the fund as a substitute for stocks, whilst other fund shareholders are inattentive to news. Appendix C.1 shows that the findings of the model are robust to this extension.[10]

4.2 Asset Price Dynamics

The dynamics of price of the risky asset class price obtain by Equation (8), as follows

$$dP = p_D dD + \theta dV.$$

Asset price dynamics are driven by the evolution of fundamentals and the wealth of static investors. Discount rates are instead fixed by the tractable CARA utility specification. By replacing in the above expression dV from Equation (5),

$$dP = p_D dD + \theta\big[rV(1-\theta)dt + Q(dP + Ddt) + \pi dF\big]. \tag{19}$$

Equation (19) highlights that the equity holdings of static investors, Q, give rise to price amplification effects.[11]

While price changes dP affect the wealth of both dynamic and static investors, their response differs. Dynamic investors with CARA preferences only revise their portfolio conditionally on the arrival of unpriced news. When faced with capital gains, dynamic investors simply increase their consumption level, c. In contrast, static investors reinvest into the risky asset class a proportion θ of their capital gains, exerting upward price pressure. This result sharply contrasts with common wisdom, since static investors rebalance their portfolio in the opposite direction of price changes. A numerical example helps to clarify this mechanism.

[10] The relationship between wealth flows and past performance was also considered. Details are available upon request.

[11] This wealth amplification effect resembles Kyle and Xiong (2001) and Basak and Pavlova (2013), but it pertains to a distinct group of investors following a static asset allocation strategy.

Example 1. Suppose $P = \$100$, $X = Q = 0.5$, and $\theta = 0.4$. As firms announce good earnings, the present value of the dividend stream increases by \$20. Dynamic investors demand more shares and the price rises to $P + dP = \$120$. Dynamic investors realize capital gains $dW = XdP = \$10$ and increase their consumption level. Static investors realize capital gains $dV = QdP =$\$10, of which $\theta dV = \$4$ are reinvested into the stock market leading to a price of \$124, which has a second-round effect on wealth, and so forth, leading to an amplification of $\frac{1}{1-\theta Q} = 1.25$. In the new equilibrium, $P = \$125$, $X = 0.56$, and $Q = 0.44$. Following a revision of the fundamentals of \$20, the price changes by \$25. Absent static investors, the price would have closed at \$120.

Example 1 shows that as the price of the risky asset class increases, static investors sell some of their shares, Q_t, trading against the price change. However, the level of their wealth investment, θV_t, increases. Ultimately, it is the wealth invested that influences security prices, rather than the number of shares traded. The example highlights the importance of the counterfactual price that would prevail in the absence of static investors.

The intuition behind this amplification mechanism is that static investors, in contrast to dynamic investors, have a predictable response to price changes, exerting procyclical price pressure in response to market movements. Earlier papers largely focused on the observation that demand unrelated to fundamentals slopes down in the price of stocks (Shleifer, 1986; Wurgler and Zhuravskaya, 2002). Less attention has been devoted to the feature that they also slope upwards in wealth. Appendix C.2 further develops the analysis in this direction.

While this argument carries important implications for empirical research in the field, it is crucial to note that, unlike the other findings in the paper, it depends on the preferences of dynamic investors being independent of their wealth. As is well known, dynamic investors with CRRA utility would also generate wealth amplification effects. Thus, it is reasonable to expect static investors to amplify price volatility when dynamic investors are less wealthy, while potentially dampening price volatility when dynamic investors are more wealthy.

4.3 Asset Classification Effects in the Treasury Market

The baseline model illustrates the "*asset classification effect*" in relation to the equity market, but fixed asset allocations target several asset classes or subsets thereof. In particular, the analysis can be extended to the bond market, which is itself subject to price pressure (D'Amico and King, 2013; Vayanos and Vila, 2021).

A simple way to extend the analysis to the Treasury market is to use a model with price pressure on the Treasury market, regarding the demand of static investors for bonds as a demand risk factor. Greenwood and Vayanos (2014) suggest that a shock to the demand factor should move the yields of all bonds in the opposite direction as the shock and the instantaneous expected returns of all bonds in the opposite direction as the shock. After an exogenous increase to the wealth passively invested, one should thus observe lower yields and bond expected returns. Appendix C.3 extends the model in this direction.

The wealth of static investors reflects the developments of the stock price, and thus generates comovement between the two markets. Previous contributions in the literature who focused on the excess comovement between stocks and bonds, such as Shiller and Beltratti (1992), Connolly, Stivers, and Sun (2005), Baele, Bekaert, and Inghelbrecht (2010), David and Veronesi (2013), and Duffee (2023), largely abstract from the price pressure resulting from static asset allocation strategies.

Figure A.3 provides evidence suggestive of the spillover of wealth effects between the U.S. equity and Treasury bond market using dividend pay dates as a clean instrument for wealth shocks unrelated to information. Days with large dividend payment amounts feature large returns on the stock market (Panel A), with low term premia (Panel B), and low expected returns on 10-year Treasury bonds (Panel C).

5 Empirical Estimation

5.1 Testable Predictions

The model generates three main empirically testable hypotheses, reported below.

Hypothesis 1: *Asset classification effect.* The aggregate value of assets within an asset class is at least as great as the wealth invested in that asset class to implement static asset allocation strategies. Proposition 1 forms the basis for this hypothesis.

Hypothesis 2: *Wealth amplification effect.* Static asset allocation strategies generate conditional price volatility in excess of the volatility of earnings, but still connected to it. This hypothesis follows from Equation 19.

Hypothesis 3: *Forecast accuracy and the risk/return trade-off.* Static asset allocation strategies reduce the forecast accuracy of stock prices for future earnings, particularly when expected returns are low and volatile. This hypothesis stems from Corollary 1.

It is briefly explained here how the elements of the model and the ensuing analysis help to set up to the empirical examination that follows thereafter. An increase in the wealth invested under static asset allocation strategies increases the demand for the risky asset class in the present as well as the forecast of its realization in the future, generating the asset classification effect outlined in Hypothesis 1. Stock price movements affect the wealth of investors with allocation mandates, who reinvest their capital in static proportions and amplify the price responses to news, leading to Hypothesis 2. The price of a stock contains information on its expected earnings, as well as on its expected future price. Hypothesis 3 follows from the fact that an increase in the wealth committed to the risky asset puts upward pressure on its price and biases its signal for prospective fundamentals, even more so when low and volatile expected returns induce dynamic investors to invest less in the risky asset and more in the safe asset.

5.2 Measurement

To model the heterogeneous composition of investors in a parsimonious manner, it is assumed that dynamic households trade on their own account to optimize their utility. In contrast, other households are less attentive to the stock market and delegate their investment decisions to professional portfolio managers, such as Mutual Funds (MFs) and Exchange-Traded Funds (ETFs). In managing the wealth of these households, investment professionals operate under asset allocation mandates, which may be driven by agency considerations, as discussed by He and Xiong (2013).

Static allocation mandates present an intriguing aspect of capital markets, by constraining a large set of investors from exploiting intertemporal changes in the investment opportunity set. This is evidenced in Figure A.1, which shows that MFs and ETFs maintain a constant asset allocation in spite of changing investment opportunities.

The paper considers the presence of investors adopting static asset allocation strategies as a given feature of the financial markets and examines the equilibrium investment policy of intertemporally optimizing investors. For the purpose of model estimation, households are treated as dynamic investors if they invest directly in stocks, while they are considered static investors if they hold assets through MFs and ETFs subject to static asset allocation mandates.

Figure A.2 plots the ownership structure of the U.S. equity market over time. The importance of delegated portfolios is on the rise, particularly after the '90s. By 2020, households only directly held around 40% of U.S. equity markets. Meanwhile, MFs and ETFs combined ownership shares approximately accounted for 35% of the total market value, with the remaining proportion of the stock market mostly held by foreign investors.

5.3 The Time Series

The theory discussed so far underscores that adequate modeling of asset price dynamics should account for the ownership structure of the stock market. As a first descriptive step of the analysis, consider a yearly data sample retrieved from Robert Shiller's website and the Fed Flow of Funds ranging from 1870 to 2021.[12] To gain intuition of the data, it is helpful to construct a *static share* variable, defined as the proportion of the U.S. stock market held by MFs and ETFs.[13] Figure 2 illustrates the positive time-series association between the static share and the price/earnings ratio, with linear correlation of 0.61. A first inspection of the data thus indicates that the static ownership share of the market correlates positively with the equity valuation multiple. In the model, this occurs since static investments affect prices, but not earnings. This simple correlation analysis goes in the direction outlined in Hypothesis 1.

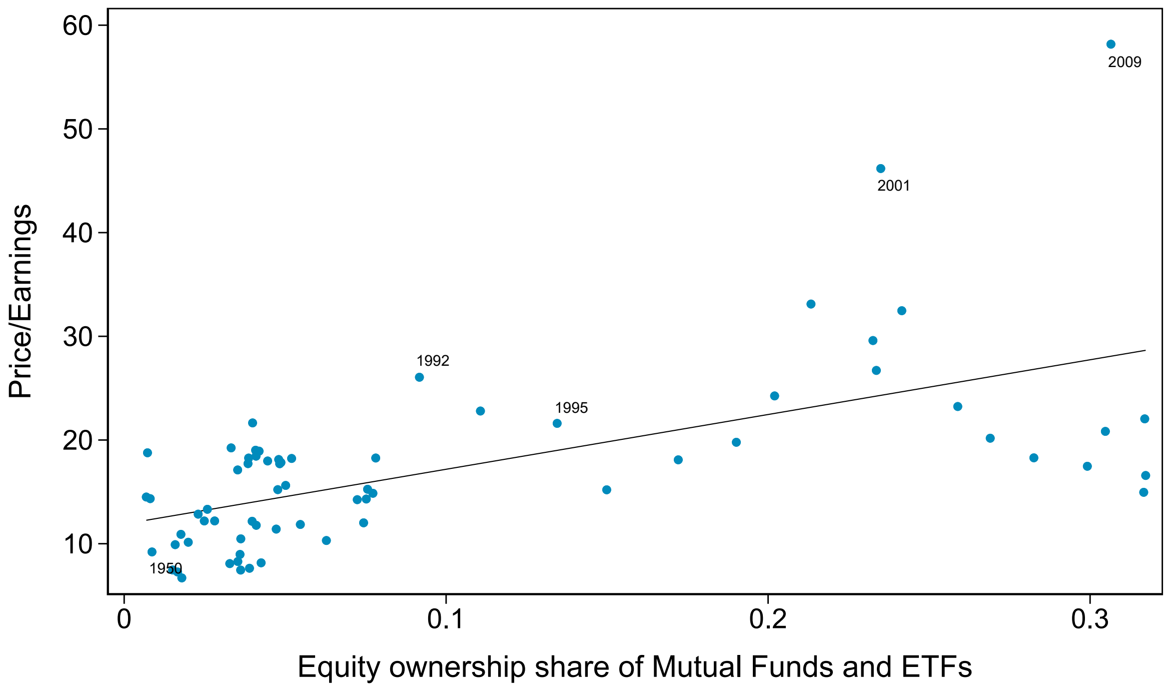

FIGURE 2: **Static Investors and Equity Valuations**. The figure shows a time series scatter plot of the price/earnings valuation multiple of the S&P500 and the equity ownership held by domestic Mutual Funds and ETFs, using yearly data from the Fed Flow of Funds and Robert Shiller's website ranging from 1870 to 2020.

In terms of time series implications, a contribution of this paper is to suggest that the

[12]Flow of Fund equity data are obtained from Table L.224 at https://www.federalreserve.gov/releases/z1.

[13]The static share variable is set to zero before 1951, when holdings data are available from the Flow of Funds.

same news may have different effects on returns depending on the *ownership structure* of the stock market – see Hypothesis 2. For example, the model suggests that unexpected good earnings should have a stronger impact when they lead to capital gains that are automatically reinvested. Mutual funds and ETFs are professional asset managers who invest a constant proportion of their wealth into equities. Figure 3 shows one measure of their importance, their ownership share of the Standard & Poor's 500, along with the index real price and earnings recorded over 150 years. The figure shows that the volatility of prices exceeds the volatility of fundamentals, but is still connected to it. Consistent with the model, the stock market ownership share of MFs and ETFs is positively correlated with the responsiveness of prices to earnings in the data. The structural breaks in the price/earnings multiple around 1954 and 1994 first documented by Lettau and Van Nieuwerburgh (2008) are a clear reflection of this amplified dependence of price on earnings, and coincide with persistent changes in the ownership structure.[14]

These consideration motivate a time series model of volatility with a structural interpretation of equity ownership data. Consider the GARCH-MIDAS specification for the volatility of stock returns proposed by Engle, Ghysels, and Sohn (2013), that blends a slow-moving component recorded at low frequency and a high-frequency conditionally autoregressive component.[15] The model reported in Equation (20) relates the returns $\mathtt{r}_{\mathtt{d,q}}$ realized on day $\mathtt{d}$ to a constant mean $\mathtt{m}$, as well as to white noise innovations $\mathtt{e}_{\mathtt{d,q}}$ that enter the specification through a component model for volatility. The long-run component $\mathtt{l}_{\mathtt{q}}$ is a function of the contemporary and lagged proportion of the U.S. stock market held by MFs and ETFs recorded on quarter $\mathtt{q}$, where $\mathtt{n}$ is the intercept and $\mathtt{f}_{\mathtt{k}}$ is a beta function weighting the $\mathtt{K}$ lags included. The short-run component is a GARCH(1,1) model with daily lagged innovations and parameters $\mathtt{a}$ and $\mathtt{b}$.

$$\begin{aligned}
\mathtt{r}_{\mathtt{d,q}} &= \mathtt{m} + \sqrt{\mathtt{l}_{\mathtt{q}}\mathtt{g}_{\mathtt{d,q}}}\mathtt{e}_{\mathtt{d,q}}, \\
\mathtt{l}_{\mathtt{q}} &= \mathtt{n} + \mathtt{c}\sum_{\mathtt{k}=1}^{\mathtt{K}} \mathtt{f}_{\mathtt{k}}(\mathtt{w}_1, \mathtt{w}_2)\text{Static Share}_{\mathtt{q}-\mathtt{k}}, \\
\mathtt{g}_{\mathtt{d,q}} &= (1 - \mathtt{a} - \mathtt{b}) + \mathtt{a}\frac{(\mathtt{r}_{\mathtt{d}-1,\mathtt{q}} - \mathtt{m})^2}{\mathtt{l}_{\mathtt{q}}} + \mathtt{b}\mathtt{g}_{\mathtt{d}-1,\mathtt{q}}.
\end{aligned} \tag{20}$$

The model in Equation (20) enables the same news to have different effects depending

[14]Previous explanations have focused on improved capital markets participation (Vissing-Jørgensen, 2002) and the prospects of higher productivity growth (Jermann and Quadrini, 2007). These earlier contributions are consistent with a Gordon model where stock prices are equal to the present discounted value of dividends.

[15]This specification is traditionally employed to evaluate the effect of macroeconomic variables on market volatility.

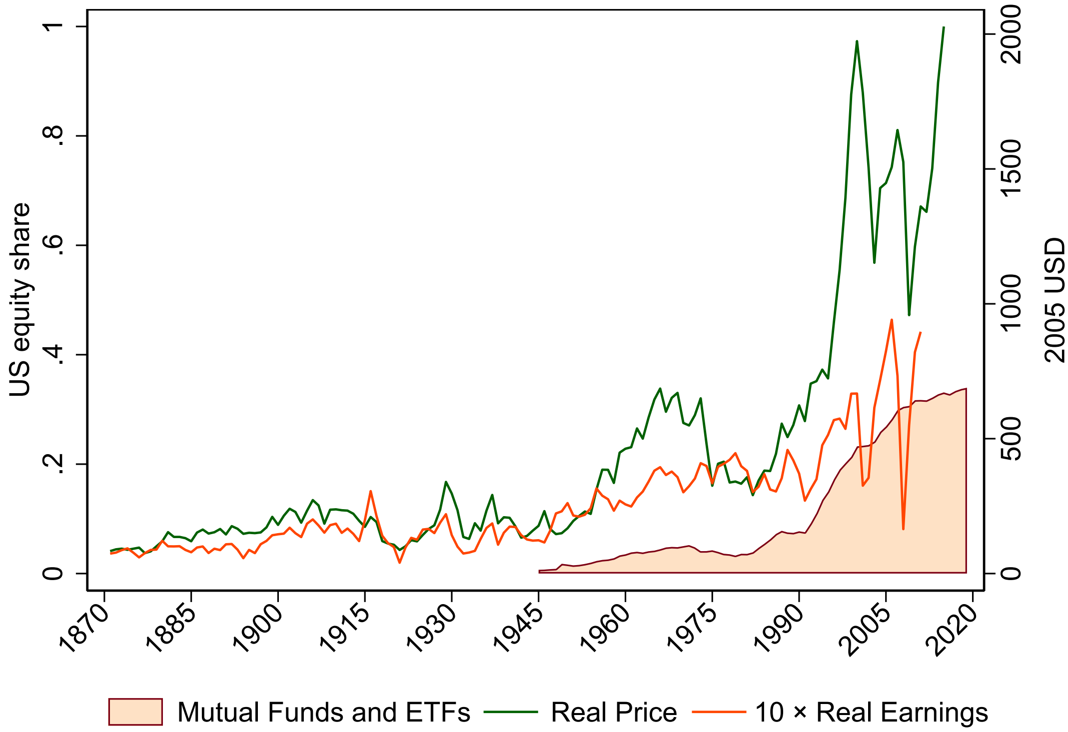

FIGURE 3: **Market Ownership, Price, and Earnings**. The figure shows the U.S. equity ownership share of domestic Mutual Funds and ETFs (left y-axis), as well as the price of the Standard and Poor's 500 and the earnings accruing to the index (right y-axis), both expressed in real terms. The data are obtained from the Fed Flow of Funds and Robert Shiller's website.

on the ownership structure of the stock market, captured by the proportion of the U.S. stock market held by MFs and ETFs in quarter $\mathtt{q}$ and denoted by Static Share$_{\mathtt{q}}$ – the same variable used in the previous Figures 3 and 2. The model of Section 2 suggests that the response of returns to news should be amplified when static investors hold a larger proportion of the stock market. In the above specification, the wealth amplification effect is directly tied to $\mathtt{c}$, that is thus expected to be positive and statistically significant.

Holdings data are readily available at the quarterly frequency from the Federal Reserve Flow of Funds statistics, and can be useful to complement workhorse time-series models of the daily volatility of aggregate returns using mixed data sampling techniques. The daily S&P 500 returns data are retrieved from Bloomberg. Table 1 presents the estimates. Panel A pertains to the baseline estimation, and Panel B presents a robustness test where the long-run component is estimated on a rolling basis. The coefficient estimate $\mathtt{c}$ has the expected sign and is both statistically significant and economically meaningful. For the full sample, the parameter estimate is 0.024 with a t-statistics of 4.7, suggesting that an increase in static ownership predicts greater volatility in the financial market for the upcoming quarter. The estimates appear remarkably robust across specifications. For example, in Panel B the estimate of $\mathtt{c}$ is again 0.024, with t-statistics of 4.6. Consistently with the proposed theory, where the amplification effect is a concave function of static ownership, the estimate of $\mathtt{c}$ is larger in the earlier 1953-1984 subsample characterized by lower levels of static ownership. On the other hand, during the 1985-2010 period the static ownership variable rises dramatically from 0.06 to 0.31, in correspondence to a long-run component coefficient estimate of 0.014.[16] The results of this analysis of volatility go in the direction outlined in Hypothesis 2.

Aggregate patterns suggest that rising static ownership is associated with a higher sensitivity of stock prices and returns to fundamentals, but should be interpreted cautiously. Further econometric analyses can be carried out in the cross section of stocks, which has the advantage of delivering a better identification.

5.4 The Cross Section

To further examine the link between stock price returns and ownership structure outlined in Hypothesis 2, this paper relies on cross-sectional regressions of abnormal returns on standardized earnings surprises around corporate announcements. Event studies around earnings announcements are a widely used empirical strategy in financial economics. These studies focus their attention on a narrow window around the event date. Take as an example Hotchkiss and Strickland (2003), who document that the investor composition matters for the response of stock prices to corporate earnings announcements. Consider the following panel regression model:

$$\begin{aligned} \text{Abnormal Return}_{it} &= b_0 + \text{Firm FE} + \text{Time FE} \; + b_1 \times \text{Earnings Surprise}_{it} \\ &+ \; b_2 \times \text{Earnings Surprise}_{it} \times \text{Wealth Benchmarked}_{it} + \varepsilon_{it}. \end{aligned} \quad (21)$$

A unit of observation is an announcement earnings of firm i at time t. For each stock, the abnormal return is estimated with respect to the constant mean model, the market model (CAPM), and the Fama and French (1992) model (FF3). Earnings surprises are calculated by taking the increase in earnings per share over four quarters and dividing it

[16] Future research could assess the forecasting performance of ownership data for volatility, using the data sampling methods discussed in Ghysels, Plazzi, Valkanov, Rubia, and Dossani (2019).

by its eight-quarters rolling standard deviation, and wealth benchmarked to each stock is the measure of Pavlova and Sikorskaya (2023). The sample construction follows standard conventions, and is described in detail in Appendix D. The working sample is a comprehensive cross section of more than 5 thousand U.S. firms observed from 1998 to 2018. Table 2 reports summary statistics of firm-level variables. In the data, earnings surprises and benchmarked wealth have average values equal to 0.29 and 0.18, respectively. However, earnings surprises have a volatility of 0.25, much higher than the volatility of benchmarked wealth, equal to 0.08. The regression model includes firm FEs to control for any time-invariant firm-specific factors such as a firm's industry. Also, time FEs are included to take care of market-wide factors like the macroeconomic environment.

The event study setup helps to pin down whether the amplification mechanism results from static wealth. Table 3 presents the results of the estimation. The effects of earnings announcements are amplified by the wealth benchmarked to the stock. The documented effect is economically large and statistically significant, as the baseline earnings response coefficient of 0.276 increases to 0.380 at the median of the distribution of benchmarked wealth, equal to 0.181. The result is robust to alternative statistical models for normal returns. This economically sizeable effect is not easy to explain using standard theories. For example, most theories of overreaction to news about fundamentals are based on the dynamic portfolio choices of extrapolating investors, and remain silent as to why *passive* investors would amplify prices response to news. In the model, this excess sensitivity of prices to earnings news is associated with a wealth amplification effect that originates from the procyclical price pressure exerted by static investors. This finding is corroborated by Sammon (2024), who uses a different sample and measure of static ownership and documents that a stock in the 90$^{\text{th}}$ percentile of static ownership responds nearly 3 times as much to earnings news as a stock in the 10$^{\text{th}}$ percentile of static ownership. To assess if the effect is persistent, Panels B and C of Table 3 assess the cumulative abnormal reaction of stock prices over progressively the longer time horizons of 3 and 7 trading days around the corporate earnings announcements. The magnitude of the coefficients is remarkably stable, and while standard errors progressively widen with the event window, the estimates remain statistically and economically significant in all specifications.

The amplification of stock price responsiveness to news and the reduction in forecast price accuracy are two sides of the same coin. By its nature, the accounting system recognizes information with a lag with respect to the stock market. Hence, when the stock price is less informative about future earnings, its responsiveness to corporate earnings reports is higher. Overall, the data are consistent with the predictions of the model.

6 Conclusion

The paper introduces a model that highlights the importance of heterogeneous asset allocation strategies for the price of financial securities. The key insight of the paper is that static asset allocation strategies drive security prices above their fundamentals. As the model shows, strategies that invest in static proportions across asset classes—despite fluctuations in their risk and returns—exert a price pressure on the securities within these asset classes. Given the persistence of this pressure, attempting to reverse its price effects is irrational. Even strategies that dynamically adjust asset allocations in response to information would find it profitable to hold assets priced above their fundamentals in the expectation to sell them at a good price. This mechanism leads to a divergence between asset prices and their discounted cash flows, which becomes more pronounced when expected returns are low and volatile. Formally, static asset allocation strategies contribute to the formation of rational price bubbles.

The paper defines the "*asset classification effect*," whereby a security's classification within an asset class attracting capital unresponsive to changes in investment opportunities has a persistent effect on the security's price. This finding constitutes a generalization of the index inclusion effect. Recent literature on the index inclusion effect has focused on the strength of the effect over time (Greenwood and Sammon, 2025) and across stocks (Pavlova and Sikorskaya, 2023). Future research could investigate the asset classification effect and its variation across different asset classes and time periods.

Appendix

A Proof of Proposition 2

As is standard in the literature, the proof proceeds by postulating that the price function is as guessed and verifies that the Hamilton-Jacobi-Bellman (HJB) equation, the market clearing condition, and the transversality conditions are satisfied in equilibrium.

$$P_t = p_\gamma + p_D D_t + p_m m + \theta V_t,$$

where $p_\gamma = -\frac{\gamma}{r^2}\left(\frac{\omega}{r} + \theta\pi\right)^2$, $p_D = \frac{1}{r}$, and $p_m = \frac{1}{r^2}$.

Price dynamics follow the Itô process

$$dP_t = p_D dD_t + \theta\big[rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi dF_t\big].$$

The state variables follow dynamics

$$\begin{aligned} dD_t &= m dt + \omega dB_t, \\ dV_t &= rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi dF_t, \end{aligned}$$

Price drift and diffusion are, respectively,

$$\mu_t = \frac{\frac{m}{r} + \theta[rV_t(1-\theta) + Q_t D_t]}{1-\theta Q_t}, \qquad \sigma_t = \frac{\frac{\omega}{r} + \theta\pi}{1-\theta Q_t}. \tag{22}$$

The Hamilton-Jacobi-Bellman (HJB) equation is

$$\begin{aligned} 0 &= \max_{\{c,X\}} U(c) + \frac{\mathbb{E}_t[dJ]}{dt} \\ &= \max_{\{c,X\}} U(c) + J_t + J_W\mathbb{E}_t[dW] + J_V\mathbb{E}_t[dV] + \frac{1}{2}J_{WW}\mathbb{E}_t[dW^2] + \frac{1}{2}\mathbb{E}_t[dV^2] + J_{WV}\mathbb{E}_t[dWdV]. \end{aligned}$$

Moreover,

$$\begin{aligned}
\mathbb{E}_t[dW] &= [rW - c + X\big(\mu - rP + D\big)]dt, \\
\mathbb{E}_t[dW^2] &= \mathbb{E}_t[(XdP)^2] = (X\sigma)^2 dt, \\
\mathbb{E}_t[dV] &= [rV(1-\theta) + Q(\mu + D)]dt, \\
\mathbb{E}_t[dV^2] &= (Q^2\sigma^2 + \pi^2)dt, \\
\mathbb{E}_t[dV dW] &= XQ\sigma^2 dt.
\end{aligned}$$

By substituting the above expressions in the HJB equation,

$$\begin{aligned}
0 &= \max_{\{c,X\}} U(c) + J_t + J_W \mathbb{E}_t[dW] + J_V \mathbb{E}_t[dV] + \frac{1}{2} J_{WW} \mathbb{E}_t[dW^2] + \frac{1}{2}\mathbb{E}_t[dV^2] + J_{VW}\mathbb{E}_t[dW dV] \\
&= \max_{\{c,X\}} U(c) + J_t + J_W\big[rW - c + X(\mu - rP + D)\big] + J_V\big[rV(1-\theta) + Q(\mu + D)\big] \\
&\qquad + \frac{1}{2} J_{WW} X^2\sigma^2 + \frac{1}{2} J_{VV}(Q^2\sigma^2 + \pi^2) + J_{WV} XQ\sigma^2.
\end{aligned}$$

The first order conditions (FOCs) are

$$\begin{aligned}
&U'(c) = J_W, \\
&X = -\frac{J_W}{J_{WW}\sigma^2}\big(\mu - rP + D\big) - \frac{J_{WV}}{J_{WW}\sigma^2} Q\sigma^2.
\end{aligned}$$

Dynamic investors have CARA utility, suggesting an educated guess for the value function

$$J(W, V, t) = -e^{-\delta t - r\gamma W - g(V) - \beta}, \tag{23}$$

thus $J_t = -\delta J$, $J_W = -r\gamma J$, $J_{WW} = (r\gamma)^2 J$, $J_V = -g'(V)J$, $J_{VV} = \big(g'(V)^2 - g''(V)\big)J$, and $J_{WV} = r\gamma g'(V)J$. Therefore, the FOCs become

$$\begin{aligned}
c(W, V) &= rW + \frac{1}{\gamma}\big(g(V) + \beta - \log r\big), \\
X(P, D, V) &= \frac{\mu - rP + D}{r\gamma\sigma^2} - \frac{g'(V)}{r\gamma} Q.
\end{aligned}$$

At this stage, it is standard to replace in the HJB the FOCs paired with the usual market clearing condition $X = 1$. However, the market clearing conditions requires $X + Q = 1$.

By replacing the expression for Q,

$$X(P,D,V) = \frac{P-\theta V}{P}, \qquad Q(P,V) = \frac{\theta V}{P},$$

or, replacing the expression of the candidate price,

$$X(P,D,V) = \frac{p_\gamma + p_D D + p_m m}{p_\gamma + p_D D + p_m m + \theta V}, \qquad Q(P,V) = \frac{\theta V}{p_\gamma + p_D D + p_m m + \theta V}.$$

The equilibrium price must ensure consistency between the market clearing condition and the FOCs of the optimization program of the dynamic investors, requiring

$$\begin{aligned} \frac{\mu - rP + D}{r\gamma\sigma^2} - \frac{g'(V)}{r\gamma}\frac{\theta V}{P} &= \frac{P-\theta V}{P}, \\ \mu - rP + D &= \frac{P - \theta V\left(1 - \frac{g'(V)}{r\gamma}\right)}{P} r\gamma\sigma^2. \end{aligned} \tag{24}$$

In the constrained equilibrium, $\theta = 0$, and the Sharpe ratio equals to the supply of bonds normalized to 1 (see Veronesi, 1999). In general, however, a portion of investors may exert price pressure unrelated to fundamentals. In order for dynamic investors to be comfortable with the equilibrium, the Sharpe ratio must decrease as price pressure increases. Let us workout the left-hand-side of Equation (24).

$$\mu - rP + D = -\frac{P}{P-\theta^2 V} r p_\gamma, \tag{25}$$

which uses the relation $\frac{1}{1-\theta Q} = \frac{P}{P-\theta^2 V}$. Turning to the right-hand-side of Equation (24),[17]

$$\frac{P - \theta V\left(1 - \frac{g'(V)}{r\gamma}\right)}{P} r\gamma\sigma^2 = \frac{P}{P-\theta^2 V} r\gamma\left(\frac{\omega}{r} + \theta\pi\right)^2.$$

Therefore, the requisite that the FOC and the market clearing condition simultaneously hold necessitates $1 - \frac{g'(V)}{r\gamma} = \theta$, satisfied when $g'(V) = (1-\theta)r\gamma$. As a result, Equation

[17]The two chains of equality are $\mu - rP + D = \frac{\frac{m}{r} + \theta[rV(1-\theta)+QD]}{1-\theta Q} - rP + D = \frac{1}{1-\theta Q}\left(\frac{m}{r} + \theta[rV(1-\theta) + QD]\right) - rP + D = \frac{1}{1-\theta Q}\left(\frac{m}{r} + \theta[rV(1-\theta) + QD] - r(P - \theta^2 V)\right) + D = \frac{1}{1-\theta Q}\left(D(\theta Q - 1) - rp_\gamma\right) + D = \frac{1}{1-\theta Q}\left(D\frac{\theta^2 V - P}{P} - rp_\gamma\right) + D = -\frac{P}{P-\theta^2 V} rp_\gamma$; and $\frac{P-\theta V\left(1-\frac{g'(V)}{r\gamma}\right)}{P} r\gamma\sigma^2 = \frac{P-\theta V\left(1-\frac{g'(V)}{r\gamma}\right)}{P} r\gamma\left(\frac{\frac{\omega}{r}+\theta\pi}{1-\theta Q}\right)^2 = \frac{P-\theta V\left(1-\frac{g'(V)}{r\gamma}\right)}{P} r\gamma\left(\frac{\frac{\omega}{r}+\theta\pi}{1-\theta Q}\right)^2 = \frac{P-\theta V\left(1-\frac{g'(V)}{r\gamma}\right)}{P} r\gamma\left(\frac{\omega}{r} + \theta\pi\right)^2\left(\frac{P}{P-\theta^2 V}\right)^2 = \frac{P-\theta^2 V}{P}\left(\frac{\omega}{r} + \theta\pi\right)^2 r\gamma\left(\frac{P}{P-\theta^2 V}\right)^2 = \left(\frac{P}{P-\theta^2 V}\right) r\gamma\left(\frac{\omega}{r} + \theta\pi\right)^2$.

(24) simplifies to

$$p_\gamma = -\frac{\gamma}{r^2}\left(\frac{\omega}{r} + \theta\pi\right)^2,$$

consistently with the definition of p_γ. In the constrained equilibrium, $\theta = 0$, and the required compensation for risk accounts for uncertainty over earnings. In the more comprehensive equilibrium with both dynamic and static investors, the required compensation for risk incorporates flow risk. Let us replace the FOCs into the HJB.

$$\begin{aligned}
0 &= \frac{1}{J}U(c^*) + \frac{1}{J}\frac{\mathbb{E}_t[dJ]}{dt} = r + \frac{1}{J}\frac{\mathbb{E}_t[dJ]}{dt} \\
&= r - \delta - r\gamma\left[\frac{1}{\gamma}(\log r - g(V) - \beta) + X^*(\mu - rP + D)\right] - g'(V)\big[rV(1-\theta) + Q(\mu + D)\big] \\
&+ \frac{1}{2}(r\gamma\sigma X^*)^2 + \frac{1}{2}\big(g'(V)^2 - g''(V)\big)(Q^2\sigma^2 + \pi^2) + r\gamma\sigma^2 g'(V)X^*Q.
\end{aligned}$$

Substituting X^*,

$$\begin{aligned}
0 &= r - \delta - r\gamma\left[\frac{1}{\gamma}(\log r - g(V) - \beta) + \left(\frac{\mu - rP + D}{r\gamma\sigma^2} - \frac{g'(V)}{r\gamma}Q\right)\big(\mu - rP + D\big)\right] \\
&- g'(V)\big[rV(1-\theta) + Q(\mu + D)\big] + \frac{1}{2}\left[r\gamma\sigma\left(\frac{\mu - rP + D}{r\gamma\sigma^2} - \frac{g'(V)}{r\gamma}Q\right)\right]^2 \\
&+ \frac{1}{2}\big(g'(V)^2 - g''(V)\big)(Q^2\sigma^2 + \pi^2) + r\gamma\sigma^2 g'(V)\left(\frac{\mu - rP + D}{r\gamma\sigma^2} - \frac{g'(V)}{r\gamma}Q\right)Q.
\end{aligned}$$

Simplifying the expression yields

$$\begin{aligned}
0 &= r - \delta - r(\log r - g(V) - \beta) - \frac{(\mu - rP + D)^2}{2\sigma^2} \\
&- g'(V)[rV(1-\theta) + Q(\mu + D) - Q(\mu - rP + D) + \frac{\pi^2}{2}] \\
&= r - \delta - r(\log r - g(V) - \beta) - \frac{(\mu - rP + D)^2}{2\sigma^2} - g'(V)[rV(1-\theta) + rQP + \frac{\pi^2}{2}].
\end{aligned}$$

Equivalently,

$$\begin{aligned}
0 &= r - \delta - r(\log r - g(V) - \beta) - \frac{(\mu - rP + D)^2}{2\sigma^2} - g'(V)[rV + \frac{\pi^2}{2}] \\
&= r - \delta - r(\log r - g(V) - \beta) - \frac{(r\gamma)^2}{2}\left(\frac{\omega}{r} + \theta\pi\right)^2 - g'(V)[rV + \frac{\pi^2}{2}].
\end{aligned}$$

We have used the equivalence $(\mu - rP + D)^2/\sigma^2 = (r\gamma)^2\big(\frac{\omega}{r} + \theta\pi\big)^2$ from the Equations (22) and (25). We further know $g(V) = (1-\theta)r\gamma V + K$, thus $g'(V) = (1-\theta)r\gamma$, and $g''(V) = 0$. After replacing $\beta = \frac{(\gamma\omega)^2}{2r} + \frac{\delta}{r} + \log(r) - 1$,

$$\begin{aligned} 0 &= r - \delta - r(\log r - g(V) - \beta) - \frac{(r\gamma)^2}{2}\left(\frac{\omega}{r} + \theta\pi\right)^2 - g'(V)[rV + \frac{\pi^2}{2}] \\ &= \frac{(\gamma\omega)^2}{2} - rK - \frac{(r\gamma)^2}{2}\left(\frac{\omega}{r} + \theta\pi\right)^2 - (1-\theta)r\gamma\frac{\pi^2}{2}. \end{aligned}$$

It is immediate to see that the guess satisfies the requisite optimality and market clearing conditions for suitable constant K. The transversality condition is respected. From Equation (23) and the investors' wealth dynamics,

$$\lim_{h\to\infty} \mathbb{E}\Big[J_{t+h}\Big] = \lim_{h\to\infty} \mathbb{E}\Big[- e^{-\delta(t+h) - r\gamma W_{t+h} - r\gamma(1-\theta)V_{t+h} - \beta}\Big] = 0.$$

The equilibrium of Lemma 1 achieves as a special case when $\theta = 0$, restraining static investors from allocating their wealth into equity markets.

Q.E.D.

B Proof of Proposition 3

Before proceeding with the formal proof, consider the following equilibria as a benchmark.

First, consider the equilibrium with only *dynamic investors*, by setting $\theta = 0$. By the optimality of dynamic investors, the price of the i-th stock takes the standard form

$$P_{it} = \mathbb{E}_t^*\left[\int_t^\infty e^{-r(s-t)} D_{is}\, ds\right] = p_{\gamma_i} + p_D D_{it} + p_m m_i,$$

where that $p_{\gamma_i} = -\frac{\gamma}{r^2}\big(\omega_i + \sum \omega_{ij}\big)$.

Second, consider the equilibrium with only *static stock pickers*, that achieves with $r \to \infty$, luring dynamic investors to the riskless asset, and $\lambda_i = 0$, excluding the stock from the index. By market clearing, the price of the i-th stock is

$$P_{it} = \hat{q}_{it}\theta V_t^A.$$

In this case, the solution of the problem of the stock picker simplifies to

$$\hat{q}_{it} = \left[\frac{m_i + D_{it}}{\gamma\omega_i^2}\frac{P_{it}}{\theta V_t^A} - \sum_{j\neq i}\frac{q_{jt}\omega_{ij}}{\omega_i^2 P_{it}P_{jt}}\right] \Big/ \sum_{j\neq i}\left[\frac{m_i + D_{it}}{\gamma\omega_i^2}\frac{P_{it}}{\theta V_t^A} - \sum_{j\neq i}\frac{q_{jt}\omega_{ij}}{\omega_i^2 P_{it}P_{jt}}\right].$$

We have cash-in-the market pricing, since $\sum P_{it} = \theta V_t^A$.

Third, consider the equilibrium with *static stock pickers and index trackers*, that achieves with $r \to \infty$, luring dynamic investors to the riskless asset, and $\lambda_i = 1$, relevant for stocks included in the index. By market clearing, the price of the i-th stock is

$$P_{it} = \hat{q}_{it}\theta V_t^A + \lambda_i\theta V_t^{IDX}.$$

There total market value of the risky asset class is $\sum P_{it} = \theta V_t$.

In the general equilibrium with *dynamic investors, static stock pickers, and index trackers*, guess that the price of the i-th stock takes the following form.

$$P_{it} = p_\gamma + p_D D_{it} + p_m m_{it} + \theta\big[\hat{q}_{it}V_t^A + \lambda_i V_t^{\mathrm{IDX}}\big].$$

Static stock pickers solve their mean-variance portfolio selection problem by setting

$$\hat{q}_{it} = \left[\frac{\mu_{it} + D_{it}}{\gamma\sigma_{it}^2}\frac{P_{it}}{\theta V_t^A} - \sum_{j\neq i}\frac{q_{jt}\sigma_{ijt}}{\sigma_{it}^2 P_{it}P_{jt}}\right] \Big/ \sum_{i\in I}\left[\frac{\mu_{it} + D_{it}}{\gamma\sigma_{it}^2}\frac{P_{it}}{\theta V_t^A} - \sum_{j\neq i}\frac{q_{jt}\sigma_{ijt}}{\sigma_{it}^2 P_{it}P_{jt}}\right].$$

The portfolio weights of index trackers are $\lambda_i = 1/N$. Static stock pickers ensure that index stocks and non-index stocks are priced consistently in the cross section. This greatly simplifies the problem of dynamic the dynamic investors, who can simply keep track of aggregate static wealth V, the state variable determining changes in the investment opportunity set over time. The sum of the wealth of static stock pickers and index trackers delivers the wealth of static investors $V = V^A + V^{IDX}$, which follows Equation (5)

$$\begin{aligned} dV &= rV(1-\theta)dt + Q(dP + Ddt) + \pi dF \\ &= rV(1-\theta)dt + \sum_i Q_i(dP_i + D_i dt) + \pi dF. \end{aligned}$$

This formulation implies $QP = \sum Q_i P_i$ and $QD = \sum Q_i D_i$. Similarly, Equation (12) implies $XP = \sum X_i P_i$ and $XD = \sum X_i D_i$. Intuitively, the aggregate exposure of investors to the equity asset class is the sum of their exposures to individual stocks. Finally, by definition of $P = \sum P_i$, we have $\mu = \sum \mu_i$ and $\sigma^2 = \mathbb{E}\big[\big(\sum dP_i\big)^2\big]$.

The HJB equation of the dynamic investors is

$$0 = \max_{\{c,X\}} U(c) + J_t + J_W \mathbb{E}_t[dW] + J_V \mathbb{E}_t[dV] + \frac{1}{2} J_{WW} \mathbb{E}_t[dW^2] + \frac{1}{2} \mathbb{E}_t[dV^2] + J_{WV} \mathbb{E}_t[dW dV],$$

where

$$dW = (rW - c)dt + \sum_i X_i[(D_i - rP_i)dt + dP_i].$$

Define the vectors $\mathbf{X} = [X_i]$ and $\mathbf{Q} = [Q_i]$ and the matrix $\Sigma = [\sigma_{ij}]$. We have

$$\begin{aligned}
&\mathbb{E}_t[dW]/dt = \big[rW - c + \sum_i X_i\big(\mu_i - rP_i + D_i\big)\big],\\
&\mathbb{E}_t[dV]/dt = [rV(1-\theta) + Q(\mu + D)],\\
&\mathbb{E}_t[dW^2]/dt = \mathbf{X}\Sigma\mathbf{X}^T = \mathbb{E}_t\left[\left(\sum_{i=1}^{I} X_i dP_i\right)^2\right] = \mathbb{E}_t[(XdP)^2] = X^2\sigma^2,\\
&\mathbb{E}_t[dV^2]/dt = \mathbf{Q}\Sigma\mathbf{Q}^T + \pi^2 = \mathbb{E}_t\left[\left(\sum_{i=1}^{I} Q_i dP_i\right)^2\right] + \pi^2 = \mathbb{E}_t[(QdP)^2] + \pi^2 = Q^2\sigma^2 + \pi^2,\\
&\mathbb{E}_t[dWdV]/dt = \mathbf{X}\Sigma\mathbf{Q}^T = \mathbb{E}_t\left[\left(\sum_{i=1}^{I} X_i dP_i\right)\left(\sum_{i=1}^{I} Q_i dP_i\right)\right] = XQ\mathbb{E}_t[dP^2] = XQ\sigma^2.
\end{aligned}$$

The value function is again $J(W,V,t) = -e^{-\delta t - r\gamma W - g(V) - \beta}$, and the FOCs of the HJB are

$$\begin{aligned}
X_{it}(P_i, D_i, V) &= -\frac{J_W}{J_{WW}}\big(\mu_{it} - rP_{it} + D_{it}\big) - \frac{\sum_j X_{jt}\sigma_{ijt}}{\sigma_{it}^2} - \frac{J_{WV}}{J_{WW}}\frac{P_{it}Q\sigma^2}{\sigma_i^2}\\
&= \frac{\mu_{it} - rP_{it} + D_{it}}{r\gamma\sigma_{it}^2} - \frac{\sum_j X_{jt}\sigma_{ijt}}{\sigma_{it}^2} - \frac{(1-\theta)P_{it}Q\sigma^2}{\sigma_{it}^2},\\
c_t(W,V) &= rW_t + \frac{1}{\gamma}\big(g(V) + \beta - \log r\big).
\end{aligned}$$

Let us replace the FOCs into the HJB.

$$\begin{aligned}
0 &= \frac{1}{J}U(c^*) + \frac{1}{J}\frac{\mathbb{E}_t[dJ]}{dt} = r + \frac{1}{J}\frac{\mathbb{E}_t[dJ]}{dt}\\
&= r - \delta - r\gamma\left[\frac{1}{\gamma}(\log r - g(V) - \beta) + \sum_i X_i^*\big(\mu_i - rP_i + D_i\big)\right] + \frac{1}{2}(r\gamma\sigma X^*)^2\\
&- (1-\theta)r\gamma\big[rV(1-\theta) + Q(\mu + D)\big] + \frac{1}{2}(1-\theta)r\gamma(Q^2\sigma^2 + \pi^2) + (r\gamma\sigma)^2(1-\theta)X^*Q.
\end{aligned}$$

The above expression coincides with the HJB derived in Appendix A if and only if

$$\sum_i X_i^* \big(\mu_i - rP_i + D_i\big) = X^*(\mu - rP + D).$$

The relationship $\sum X_i P_i = XP$ directly implies $r\sum_i X_i^* P_i = rX^*P$. Moreover, since $X_i^*\mathbb{E}[dP_i] = X^*\mathbb{E}[dP]$, we have $\sum_i X_i^*\mu_i = X^*\mu$. Finally, $\sum X_i D_i = XD$ implies that the above condition holds. Therefore, the argument used in the proof of Proposition 1 applies, the HJB is solved by the optimal choice of dynamic investors, the transversality condition is respected, and the guess for the price is verified, completing the proof. Q.E.D.

C Extensions and Generalizations

C.1 Wealth Flows and Earnings News

Guess the price is again given by

$$P_t = p_\gamma + p_D D_t + p_m m + \theta V_t.$$

Consider the price dynamics and replace Equation (18) into Equation (5) to obtain

$$\begin{aligned} dP_t &= p_D dD_t + \theta\big[rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi \overbrace{\left(\rho dD + \sqrt{1-\rho^2}dZ_t\right)}^{dF_t}\big] \\ &= (p_D + p_R)dD_t + \theta\big[rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi_R dZ_t\big], \end{aligned}$$

where $p_R = \theta\pi\rho$ and $\pi_R = \pi\sqrt{1-\rho^2}$. These dynamics generalize the baseline model, since dF is correlated with dB, but follow similar structure. In light of the above, the guess can be equivalently parameterized by

$$P_t = p_\gamma + (p_D + p_R)D_t + p_m m + \theta\tilde{V}_t,$$

with the convenient redefinition of state variable dynamics, $\tilde{V}$, so that

$$d\tilde{V} = \theta\big[r\tilde{V}_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi_R dZ_t\big],$$

Price drift and diffusion are, respectively,

$$\mu_t = \frac{m(p_D + p_R) + \theta[r\tilde{V}_t(1-\theta) + Q_t D_t]}{1 - \theta Q_t}, \qquad \sigma_t = \frac{\omega(p_D + p_R) + \theta\pi_R}{1 - \theta Q_t}.$$

The HJB equation is

$$0 = \max_{\{c,X\}} U(c) + J_t + J_W \mathbb{E}_t[dW] + J_{\tilde{V}} \mathbb{E}_t[d\tilde{V}] + \frac{1}{2} J_{WW} \mathbb{E}_t[dW^2] + \frac{1}{2} \mathbb{E}_t[d\tilde{V}^2] + J_{WV} \mathbb{E}_t[dW d\tilde{V}].$$

The problem is traced back to the baseline model and the guess is verified by the steps outlined in Appendix A.

Q.E.D.

C.2 Asset Price Dynamics

Asset price dynamics obtain by replacing the dynamics of dividends, dD_t, and those of the wealth dynamics of static investors, dV, into Equation (19),

$$dP_t = A_t \left(\frac{m}{r} + \theta \big[rV_t(1-\theta) + Q_t D_t \big] \right) dt + A_t \left(\frac{\omega}{r} dB_t + \theta \pi dF_t \right), \tag{26}$$

where $A_t = 1/(1 - \theta Q_t)$ denotes the wealth amplification effect associated with static asset allocation strategies. In equilibrium, stock price dynamics result from two distinct processes, representing economic fundamentals and static demand for stocks. Accordingly, the risky asset's price drift is composed of the discounted earnings drift $\frac{m}{r}$ and the predictable evolution of price pressure, which results from the proceeds of the wealth invested in the bond market $rV_t(1-\theta)$ as well as from the dividends distributed to static investors $Q_t D_t$. Simply put, strong earnings deliver handsome dividends, a share of which is mechanically reinvested and contributes to generate upward price pressure.

Interestingly, even when predictable dividends are distributed, their reinvestment by static investors generates price pressure. The logic is simply that the foreseeable effects of future dividend distributions and associated investments are already priced – the problem of dynamic investors and the resulting equilibrium price explicitly account for these price dynamics. Thus, the occurrence of trades might still significantly move prices, even if known in advance.[18]

[18] This mechanism speaks to the findings of Hartzmark and Solomon (2022), who document that days in the top quintile of dividend payments are associated with higher market returns. The dividend amount is determined ahead of the payout date, and hence the effect cannot be ascribed to information. Relatedly, Berkman and Koch (2017) document abnormal returns and trading volume around the dividend payout dates of stocks of firms with dividend reinvestment plans.

The volatility of price changes responds both to the uncertainty over the evolution of economic fundamentals $\frac{\omega}{r}$, as well as to the risk of wealth flows, a proportion $\theta\pi$ of which may affect asset prices introducing non-fundamental volatility, in line with the empirical findings of Ben-David, Franzoni, and Moussawi (2018), who show that ETF ownership increases volatility and introduces undiversifiable risk. The importance of either of the two forces interacts with the composition of demand, as illustrated by the amplification of both the drift and diffusion by the factor A_t, which quantifies the "feedback loop" between the asset price movements and the investment decisions of the static investors. When the market is mostly held by static investors, price movements and volatility thereof are amplified by procyclical price pressure. As the proportion of the risky asset held by static investors becomes small, instead, the solution approaches the equilibrium in Lemma 1, from which might in general differ as flow risk commands a compensation even in the absence of immanent price pressure.

The amplification effect A_t of the static asset allocation strategy on the dynamics of the risky asset dP_t varies in the time series. Specifically, these effects are stronger when static investors own a larger proportion of the stock market Q_t.

This property highlights that the magnitude of the reaction of the stock price to innovations, whether regarding news about economic fundamentals or wealth flows to static investors, depends on the ownership structure of the market. When static investors hold large shares of the market, the proceeds of upward price revisions are reinvested, resulting in mounting demand pressure that amplifies the price increase. The effect is entirely symmetric. Moreover, when prices deviate from fundamentals the equity valuation ratio $\frac{P}{E}$ rises in the price pressure exerted by static investors and features meaningful variation in the time series.

Moreover, static asset allocation strategies intensify the price volatility of risky assets, σ_t. A higher ownership share static investors, Q_t, strengthens the amplification dynamics A_t and thus induces higher price volatility. Volatility reflects two sources of risk, dB for earnings and dF for capital flows, and is both stochastic and predictable, since the ownership structure of the market belongs to the information set of market participants, $Q_t \in \mathscr{F}_t$. After dynamic investors observe a large drop in the stock price, a publicly available signal, their optimal forecast of the distribution of price changes features higher volatility and fatter tails, inducing more conservative portfolio choices. As a result, the model generates volatility clusters. The price dynamics are best considered in combination with the portfolio holdings in Equation (10), according to which the proportion of the market held by dynamic investors is higher when fundamentals are strong, in which case the conditional price volatility becomes lower going forward.

Following standard conventions, μ_t denotes the drift of stock price changes and σ_t denotes their volatility. The drift and volatility of *returns* are obtained by dividing these quantities by the price level, P_t. Thus, in line with previous literature, when the market price is high, both the expected returns and the volatility are low, consistently with the well-documented tendency of stocks with high valuations to have low expected returns.[19] Moreover, demand pressure generates asymmetric features in the behavior of volatility, which spikes when the market tanks.[20] Static allocation rules may thus help to explain the asymmetric behavior of volatility. While high market prices have a calming effect on the volatility of returns, this effect is stronger when prices are upheld by fundamentals as opposed to high prices sustained by demand forces.

In the presence of static investors, stock prices are more sensitive to news when the Sharpe ratio of the equity asset class is lower. This occurs because as dynamic investors fly to the safety offered by the risk-free asset, static investors own a comparatively larger proportion of the market, and thus the procyclical price pressure exerted by the automatic reinvestment of their capital gains and losses becomes more important for asset prices. As a result, the amplification of news resulting from static investors is stronger during downturns.

The importance of dynamic investors in the transmission of financial crises through risk premia effects, is extensively studied in the literature. However, this paper is the first to point out that the stronger amplification of financial fluctuations during downturns also originate from static investors. Intuitively, static investors remain exposed to the equity asset class even during crises, when their procyclical price pressure becomes more important for the valuation of securities. This result requires a model where the static investments are priced in the stock market, and the dynamics of the wealth of static investors is endogenous to asset prices.

C.3 The Treasury Market

In the context of the model derived in this paper, asset allocation strategies require static investors to invest a fixed proportion of their wealth $(1-\theta)V_t$ in the bond market, which thus exerts price pressure on the Treasury price. The main difference relative to

[19] The exposure of stocks to demand pressure is associated with lower expected returns in related contributions, such as Koijen and Yogo (2019) and Pavlova and Sikorskaya (2023).

[20] This property is sometimes referred to as the leverage effect, because when prices are low firm leverage increases along with uncertainty (Black, 1976). More recently, Hasanhodzic and Lo (2019) have documented that the inverse relation between stock price and return volatility is not specific to firms with leverage.

Greenwood and Vayanos (2014) is that the price pressure V_t represents here a demand factor rather than a supply factor. The maintained assumption on the bond market is that dynamic investors have agile demand which does not separate prices from fundamentals, while static investors do not attempt to time the bond market. The contribution is to model the demand for bonds resulting from wealth effects on the stock market.

Greenwood and Vayanos (2014) suggest that a shock to the demand factor should move the yields of all bonds in the opposite direction as the shock. Moreover, a shock to the demand factor should the instantaneous expected returns of all bonds in the opposite direction as the shock. After an exogenous increase to the wealth passively invested, one should thus observe lower yields and bond expected returns. Hartzmark and Solomon (2022) document that days in the top quintile of dividend payments are associated with higher market returns. The amount of dividends is determined ahead of the dividend pay date, and hence the effect documented cannot be ascribed to information. The impact of dividend price pressure has increased since 1990, as static mutual funds and ETFs have become a larger component of equity holdings. Dividend payout days are thus of interest for the assessment of wealth effects. Figure A.3 provides evidence suggestive of the spillover of wealth effects between the U.S. equity and Treasury bond market using dividend pay dates as a clean instrument for wealth shocks unrelated to information. The pattern revealed by the data is clear and sizeable. Days with large dividend payment amounts feature large returns on the stock market (Panel A), with low term premia (Panel B), and low expected returns on 10-year Treasury bonds (Panel C).

D Data Description

The event study around earnings announcements is conducted using daily stock information from CRSP, quarterly "street" earning reports from the actuals I/B/E/S files, balance sheet variables from COMPUSTAT quarterly, and benchmarking intensity data from Pavlova and Sikorskaya (2023).

Filters are standard, requiring CRSP ordinary stocks (share code 10 and 11) from the daily security file to trade on NYSE, AMEX, or Nasdaq (exchange codes 1, 2, and 3). The three models for normal returns are the benchmark stock-level constant mean, the CAPM, and the Fama-French 3 factor model. The advantage of the former is to minimize estimation noise. The latter two specifications are estimated on a rolling window of 1 year and lagged by 1 quarter from the event date. The residuals of these models are the abnormal returns. The quarterly earnings per share (EPS) from I/B/E/S is used to construct standardized unexpected earnings (SUE), measured as the increment in EPS over four quarters divided by their rolling standard deviation estimated over 8 quarters. Earnings reported on weekends or on weekdays after 16:00 Eastern Time are imputed to the first date on which is possible to trade on the information. Benchmarking intensity is recorded at the yearly frequency and at the stock level every June from 1998 to 2018. The variable is defined as the cumulative weight of a stock across benchmarks scaled by the amount of assets following each benchmark and divided by the market capitalization of the stock, and thus directly maps to $Q = \theta V/P$.

To reduce the influence of outliers, each quarter the SUE observations above and below three standard deviations from the mean are dropped. To alleviate the effects of microcaps and estimation noise, every year the observations below the 5^{th} percentile of market value are dropped, as in Jegadeesh and Titman (2001), and abnormal returns are winsorized at the 1^{st} and 99^{th} percentiles. The final sample is composed of 5,568 firms for the constant mean model, which does not require rolling estimates, and 5,516 firms for the CAPM and FF3 models, the estimates of which require 250 valid trading days per company. The sample offers thus a good representation of the universe of U.S. stocks during the past two decades.

TABLE 1: **Parameter Estimates of GARCH-MIDAS with Static Holdings.** The Table presents parameter estimates of the component model relating volatility realized on day $\mathtt{d}$ to its lags and a long-run component of the proportion of the U.S. stock market held by MFs and ETFs in quarter $\mathtt{q}$. The data are from Bloomberg and the Flow of Funds, both variables are expressed in percentage terms, and numbers in parentheses are robust t-statistics.

PANEL A: FIXED LONG-RUN COMPONENT

Sample	$\mathtt{m}$	$\mathtt{a}$	$\mathtt{b}$	$\mathtt{c}$	$\mathtt{w}_1$	$\mathtt{w}_2$	$\mathtt{n}$	LLF/BIC
1951-2019	0.06494	0.08811	0.90279	0.02398	47.224	2.111	0.77061	-19247.1
	(11.472)	(42.374)	(341.23)	(4.709)	(0.0020)	(0.0009)	(9.0894)	38562.5
1953-1984	0.06036	0.08365	0.90796	0.10584	1.0014	49.84	0.33247	-7446.29
	(7.9467)	(18.027)	(178.36)	(1.6083)	(0.0179)	(0.0019)	(1.5682)	14955.5
1953-2010	0.06407	0.08052	0.91165	0.05200	48.918	49.51	0.60517	-16429.4
	(10.485)	(41.639)	(358.17)	(4.8109)	(0.0875)	(0.0862)	(7.345)	32925.9
1985-2010	0.06273	0.06210	0.92964	0.01406	37.334	49.773	0.91895	-7506.17
	(5.4763)	(15.001)	(197.23)	(1.961)	(0.0224)	(0.0227)	(5.8952)	15073.9

PANEL B: ROLLING LONG-RUN COMPONENT

Sample	$\mathtt{m}$	$\mathtt{a}$	$\mathtt{b}$	$\mathtt{c}$	$\mathtt{w}_1$	$\mathtt{w}_2$	$\mathtt{n}$	LLF/BIC
1951-2019	0.06495	0.08819	0.90267	0.02437	44.66	17.662	0.77657	-19247.3
	(11.498)	(42.348)	(340.77)	(4.5952)	(0.0326)	(0.0330)	(9.4833)	38562.8
1953-1984	0.06034	0.08370	0.90791	0.10727	1.7811	49.884	0.3278	-7446.23
	(7.9491)	(17.882)	(176.58)	(1.6381)	(0.0384)	(0.0352)	(1.5766)	14955.4
1953-2010	0.06404	0.08046	0.91171	0.05280	40.498	49.881	0.60621	-16429.4
	(10.486)	(41.221)	(358.3)	(4.5349)	(0.0757)	(0.0777)	(7.2433)	32925.9
1985-2010	0.06273	0.06209	0.92964	0.01487	37.947	49.754	0.9076	-7506.1
	(5.4728)	(15.025)	(198)	(1.9869)	(0.0214)	(0.0217)	(5.5916)	15073.7

The specification is:

$$\mathtt{r}_{\mathtt{d,q}} = \mathtt{m} + \sqrt{\mathtt{l}_{\mathtt{q}}\mathtt{g}_{\mathtt{d,q}}}\mathtt{e}_{\mathtt{d,q}},$$

$$\mathtt{l}_{\mathtt{q}} = \mathtt{n} + \mathtt{c}\sum_{\mathtt{k}=1}^{\mathtt{K}} \mathtt{f}_{\mathtt{k}}(\mathtt{w}_1, \mathtt{w}_2)\text{Static Share}_{\mathtt{q}-\mathtt{k}},$$

$$\mathtt{g}_{\mathtt{d,q}} = (1 - \mathtt{a} - \mathtt{b}) + \mathtt{a}\frac{(\mathtt{r}_{\mathtt{d}-1,\mathtt{q}} - \mathtt{m})^2}{\mathtt{l}_{\mathtt{q}}} + \mathtt{b}\mathtt{g}_{\mathtt{d}-1,\mathtt{q}}.$$

The beta weighting function $\mathtt{f}_{\mathtt{k}}$ has $\mathtt{K} = 16$ lags, $\mathtt{r}_{\mathtt{d,q}}$ is the S&P 500 return. The innovation $e_{\mathtt{d,q}}$ is white noise, Static $\text{Share}_{\mathtt{q}}$ is the proportion of the stock market held by mutual funds and exchange-traded funds, and the remaining terms are parameters.

Table 2: **Descriptive Statistics.** The Table presents summary statistics of the sample of corporations used in the event study. Balance sheet variables are from Compustat. Earnings per Share is from I/B/E/S, and Standardized Unexpected Earnings are computed as the yearly difference in Earnings per Share divided by their eight-quarters trailing volatility. Benchmarking Intensity is the measure of wealth tracking each stock proposed by Pavlova and Sikorskaya (2023). The sample runs from 1998 to 2018.

Variable	Observations	Mean	Median	Std. Dev.	Skewness
Total Assets	126,803	12710.37	1583.92	83497.32	19.39
Total Liabilities	126,768	9998.765	890.85	74809.12	19.79
Earnings per Share	125,124	1.498261	1.2490	3.826793	14.88
Benchmarking Intensity	135,582	0.179089	0.1894	0.079325	-0.55
Standardized Unexpected Earnings	135,582	0.289230	0.2515	1.686929	-0.23

Table 3: **Event Study around Earnings Announcements.** The Table presents the result of a regression of daily abnormal returns and cumulative abnormal returns on standardized earnings surprises and its interaction with the wealth passively tracking the stock. A unit of observation is an announcement of earnings of a U.S. company reported between 1998 and 2018. The numbers in parentheses are robust standard errors.

Panel A: Abnormal Returns

	Constant Mean		CAPM		FF3	
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings Surprise$_{it}$	0.276***	0.280***	0.280***	0.285***	0.281***	0.287***
	(0.034)	(0.034)	(0.035)	(0.036)	(0.036)	(0.036)
Earnings Surprise$_{it}$ × Wealth Benchmarked$_{it}$	0.577***	0.575***	0.514***	0.513***	0.510***	0.507***
	(0.174)	(0.175)	(0.182)	(0.182)	(0.183)	(0.183)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Year	Quarter	Year	Quarter	Year	Quarter
No. Obs.	135,577	135,577	124,468	124,468	124,468	124,468
$\overline{R}^2$	0.010	0.013	0.012	0.014	0.012	0.014
Firms	5,568	5,568	5,516	5,516	5,516	5,516

Panel B: CAR(-1, 1)

	Constant Mean		CAPM		FF3	
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings Surprise$_{it}$	0.334***	0.335***	0.336***	0.338***	0.335***	0.339***
	(0.037)	(0.038)	(0.038)	(0.038)	(0.039)	(0.039)
Earnings Surprise$_{it}$ × Wealth Benchmarked$_{it}$	0.472**	0.481**	0.423**	0.434**	0.429**	0.438**
	(0.188)	(0.188)	(0.194)	(0.194)	(0.195)	(0.195)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Year	Quarter	Year	Quarter	Year	Quarter
No. Obs.	135,577	135,577	124,468	124,468	124,468	124,468
$\overline{R}^2$	0.011	0.019	0.018	0.023	0.018	0.021
Firms	5,568	5,568	5,516	5,516	5,516	5,516

Panel C: CAR(-3, 3)

	Constant Mean		CAPM		FF3	
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings Surprise$_{it}$	0.374***	0.380***	0.374***	0.378***	0.385***	0.391***
	(0.042)	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)
Earnings Surprise$_{it}$ × Wealth Benchmarked$_{it}$	0.479**	0.475**	0.445**	0.458**	0.397*	0.407*
	(0.211)	(0.210)	(0.219)	(0.219)	(0.221)	(0.221)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Year	Quarter	Year	Quarter	Year	Quarter
No. Obs.	135,577	135,577	124,468	124,468	124,468	124,468
$\overline{R}^2$	0.012	0.030	0.034	0.043	0.033	0.040
Firms	5,568	5,568	5,516	5,516	5,516	5,516

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Internet Appendix for
"Asset Pricing with Dynamic and Static Investors"

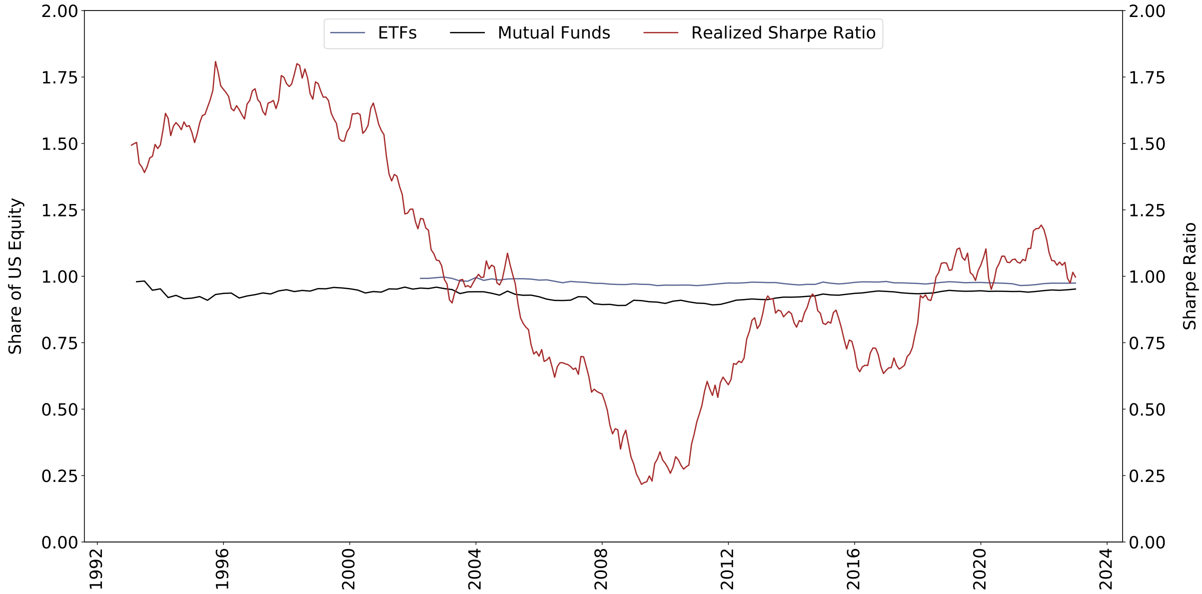

Figure A.1: **Funds' Asset Allocation and the Investment Opportunity Set**. The figure shows the average share of U.S. Equity held by Mutual Funds and ETFs using monthly data from Morningstar (left y-axis) and the monthly realized Sharpe ratio using data from CRSP and the from Kenneth French data library (right y-axis). The sample includes the universe of funds classified as U.S. Equity, Sector Equity, Allocation, and International Equity. The U.S. Equity shares are aggregated with weights corresponding to the assets under management of the fund. The realized Sharpe ratio of the U.S. Equity asset class is computed as the monthly return on the value-weighted CRSP index in excess of the risk-free rate, divided by the one-year rolling volatility of returns.

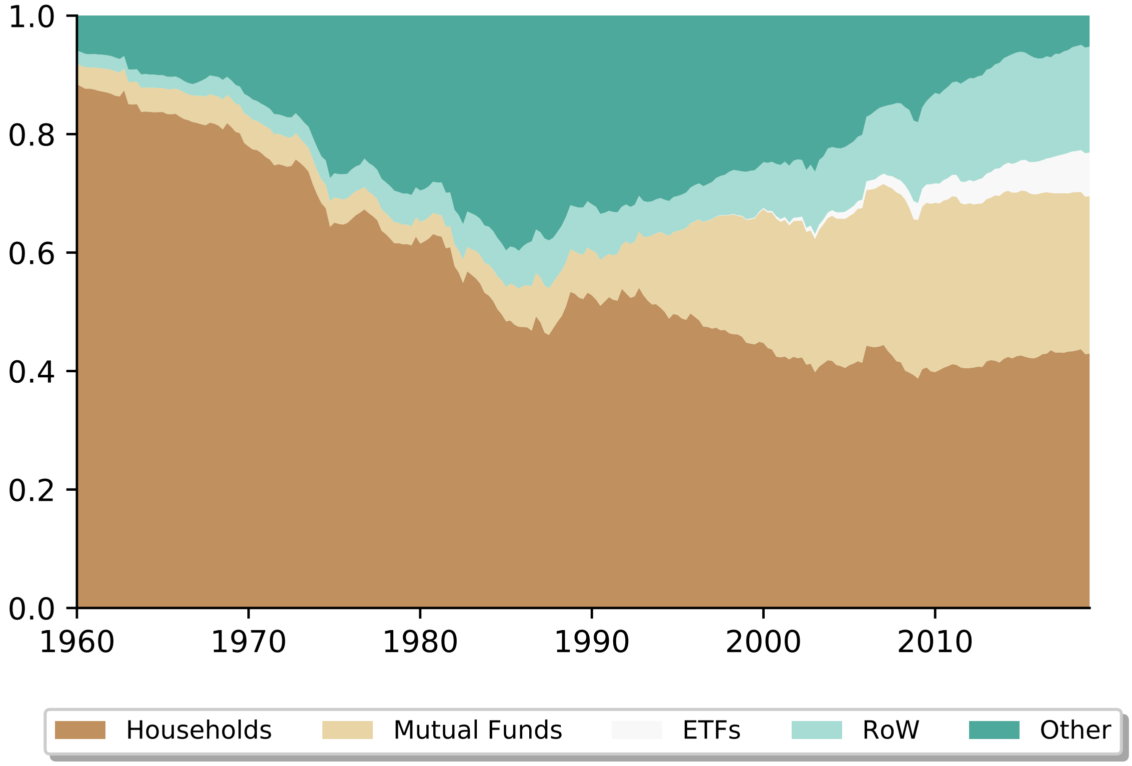

Figure A.2: **U.S. Equity Ownership**. The figure shows the composition of investors in U.S. corporate equities using Financial Account data from the Fed. RoW denotes rest of the world.

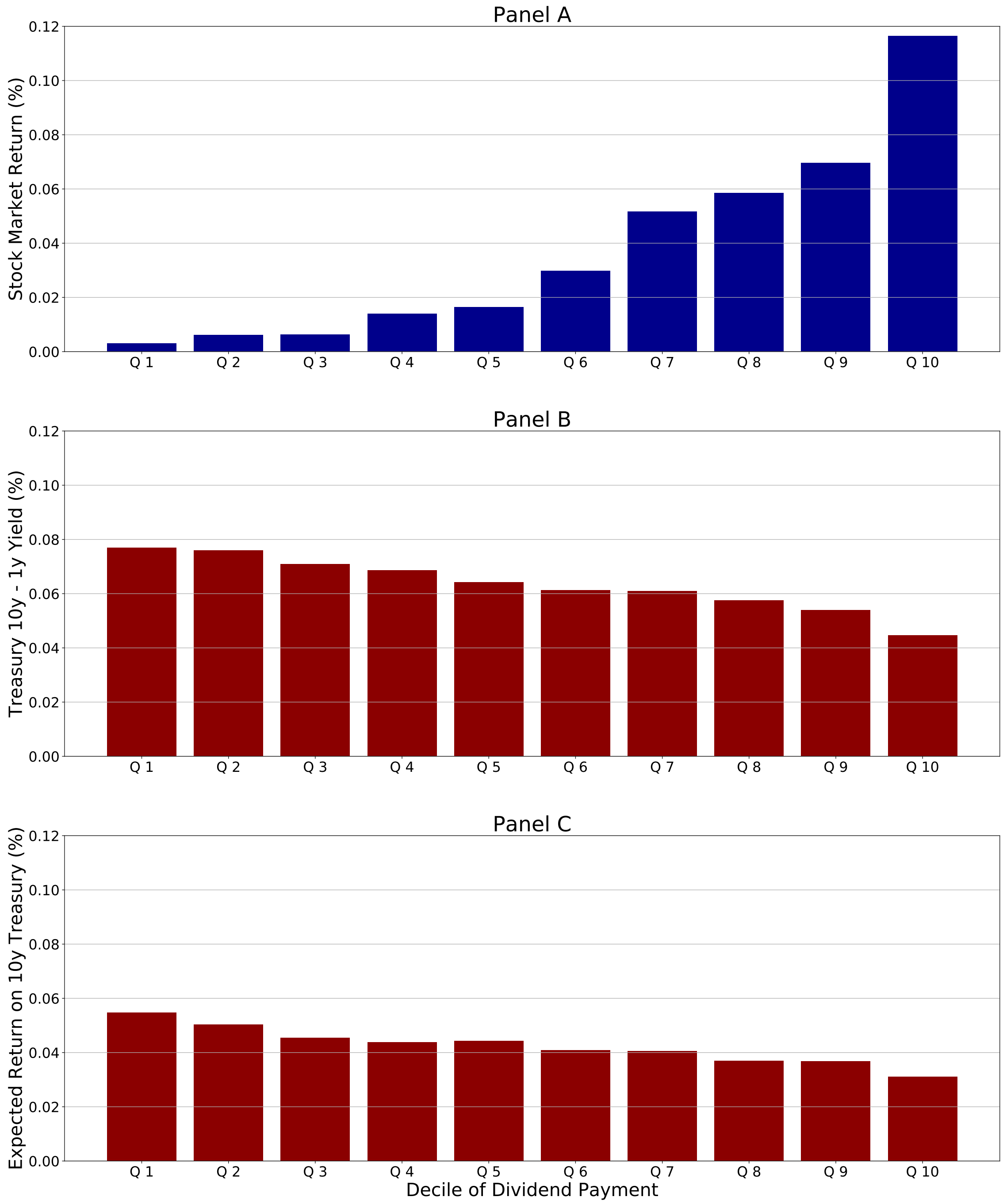

FIGURE A.3: **Wealth Effects in Equity and Treasury Markets**. Trading days are grouped into deciles by dividend payment amount, which are reported on the x-axis. Panel A: the y-axis shows the value-weighted market return, averaged within each decile. Panel B: the y-axis shows the return on the 10-year U.S. Treasury in excess of the 1-year U.S. Treasury, averaged within each decile. Panel C: the y-axis shows the expected return on the 10-year U.S. Treasury, averaged within each decile. Daily data from CRSP and Gürkaynak, Sack, and Wright (2007).