Asset Pricing with Dynamic and Static Investors

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ABSTRACT

A central assumption in asset pricing theories is that investors engage in dynamic portfolio choice. This assumption is violated when some investors adopt static asset allocation strategies. This paper presents a tractable model with dynamic investors, whose asset allocation responds to news, alongside static investors, whose asset allocation remains constant despite changing investment opportunities. Static investors maintain a constant proportion of wealth allocated to stocks, even when bond yields rise. The model reveals that static asset allocation strategies drive the aggregate valuation of the individual securities classified within target asset classes beyond risk-adjusted fundamentals, generating a rational asset price bubble.

JEL classification: G11, G12, G14, G23.

Keywords: Asset pricing, asset allocation, portfolio choice, market impact.

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I would like to thank Klaus Adam, Rui Albuquerque, Patrick Augustin, Giovanni Cocco (discussant), Bernard Dumas (discussant), Andrew Ellul, Francesco Franzoni, Xavier Gabaix, Fabio Girardi, Florian Heider, Alexander Hillert, Benjamin Holcblat (discussant), Evan Jo, Paul Karehnke, Holger Kraft, Carmelo Latino, Andrea Modena, Marco Pagano, Loriana Pelizzon, Vincenzo Pezone, Alberto Plazzi, Tarun Ramadorai, Max Riedel, Daniel Schmidt, Christian Schlag, Stephan Siegel, Marti Subrahmanyam, and conference and seminar participants at the Bank of Italy, Bayes Business School, Boston College Carroll School of Management, École Supérieure de Commerce de Paris, Finance Theory Group Summer Conference, Finanche Theory Group Summer School, Goethe University Frankfurt, Imperial College Business School, Leibniz Institute for Financial Research SAFE, Nova School of Business and Economics, Norwegian School of Economics, Rotterdam School of Management, University of Mannheim, USI Lugano, Venice Finance Workshop, and Warwick Business School for their valuable comments, NYU Stern for the hospitality during the initial stage of this research, and the Leibniz Institute for Financial Research SAFE for generous research support. This work was awarded as the John A. Doukas best Ph.D. paper at the European Financial Management Association Conference and as the best Ph.D. paper at the 6th Asset Pricing Conference hosted by the Long-Term Investors at Collegio Carlo Alberto. Errors are the author's sole responsibility.

1 Introduction

Most theories of asset pricing postulate that market prices are determined by agents who continuously optimize their asset allocation. Following the approach of Merton (1973), numerous studies consider asset prices as 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 broad group of investors deviate from dynamic optimization by adopting a static asset allocation strategy. Investors relying on this strategy rebalance their portfolios to maintain a constant asset allocation, despite changes in the investment opportunity set that may occur over time. Static asset allocation strategies are commonly recommended by professional advisers (Canner, Mankiw, and Weil, 1997). For example, a frequent recommendation is to hold a balanced portfolio with a 60/40 allocation between stocks and bonds.

By emphasizing the dynamic optimization of agents, standard theories of asset pricing devote limited attention to important considerations, such as whether static asset allocation strategies influence market prices, and when this effect might be most pronounced. As a step in this direction, this paper presents a tractable theory in which asset prices result from the interaction of investors using heterogeneous asset allocation strategies.

The contribution of the paper is to show that static asset allocation strategies give rise to a rational asset price bubble in the securities classified within target asset classes. This finding, referred to in what follows as the *asset classification effect*, suggests that the level of wealth allocated to an asset class through static asset allocation strategies affects the aggregate valuation of its constituent securities, over and above their expected cash flows and the discount rates applied by investors. To the best of my knowledge, this effect has not been previously articulated in the literature, despite its simplicity.

The *asset classification effect* offers a generalization of the *index inclusion effect*, the long-recognized tendency for a security's price to rise when included in an index. The general idea is fairly simple: just as the inclusion of a security in an index attracts index-tracking investors, the classification of a security within an asset class draws investments from static asset allocation strategies. In both cases, the demand for securities unrelated to future fundamentals drives asset prices above their discounted cash flows. However, rather than the price of specific securities, the asset classification effect influences the combined price of all of the securities classified within an asset class.

To develop intuition, the model considers a risk-free bond and a set of risky stocks that distribute stochastic dividends. As a group, the stocks form the equity asset class. Agents fall into two categories, distinguished by their asset allocation strategies – dynamic investors and static investors. Dynamic investors optimally revise their asset allocation upon the arrival of information to the market. Static investors maintain a fixed allocation between the bond and the equity asset class, regardless of intertemporal changes in the volatility of equity assets and in their expected returns in excess of the risk-free rate.

The asset classification effect can be demonstrated through the analysis of investors' responses to news, facilitated by the analytical solutions of the model. Following negative news about the stock market, dynamic investors reduce their allocation to the equity asset class, driving down stock prices. In contrast, static investors maintain a constant allocation to the equity asset class, cushioning the price of the securities it comprises. Through time, static investors consistently enforce an asset allocation that is unresponsive to new information, fostering the rational expectation of persistent deviations between the aggregate valuation of the equity asset class and the underlying economic fundamentals.

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). This paper shows that the adoption of static asset allocation by some agents, in deviation from dynamic optimization, generates a rational bubble. Accordingly, the theory predicts that the aggregate valuation of stocks rises with the wealth allocated to the equity asset class through static asset allocation strategies. This effect is relatively more important when expected excess returns on equity assets are low and volatile, at which point dynamic investors shift their investments toward the bond market.

The asset classification effect is consistent with the empirical evidence reported by Da, Larrain, Sialm, and Tessada (2018), who examine the reallocation of wealth between static asset allocation funds with different equity and bond targets in a setting plausibly unrelated to fundamental information. Their results indicate that the reallocation of wealth across asset classes generates price pressure on the aggregate stock market.

Thanks to its tractability, the model extends to the cross section of stocks. In this extension, investors are classified as either active stock pickers or passive index trackers. Cross-sectional portfolio constraints affect the relative price of index and non-index stocks, generating the index inclusion effect. By contrast, market-timing portfolio constraints inherent in static asset allocation strategies impact the aggregate stock market valuation for a given interest rate in the bond market, generating the asset classification effect.

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).

Notwithstanding the widespread adoption of the static asset allocation strategy, theoretical exploration of its impact on asset prices remains limited. Chien, Cole, and Lustig (2011) show that heterogeneous asset allocation strategies help to match asset prices and the distribution of household wealth. In their setup, agents trade state-contingent bonds with finite maturity, which rule out rational bubble considerations that are central to this paper. Gabaix and Koijen (2022) show that wealth flows into static asset allocation investment funds create market impact due to the absence of arbitrageurs to accommodate the resulting demand. This paper proposes a distinct principle whereby, even in the presence of unconstrained agents, the intertemporal consistency of the static asset allocation strategy creates rational expectations of asset price deviations from their discounted fundamentals. Guided by this insight, this is the first paper to introduce the asset classification effect and explore its relationship with the price of individual securities.

The effect of demand forces on asset prices was first explored in the cross section of stocks by Harris and Gurel (1986) and Shleifer (1986). Recent related literature includes Pavlova and Sikorskaya (2023), Greenwood and Sammon (2025), and Haddad, Huebner, and Loualiche (2021). Boyer (2011) examines groups of stocks with the same style label. This paper extends this line of research beyond the cross section by examining investment strategies of static wealth allocation across asset classes, which can be of importance for the pricing of stocks independently of their inclusion in indices or categories. By doing so, the paper offers a theoretical perspective intended to complement the empirical literature on the effect of demand forces on the price level of the aggregate stock market, which includes Warther (1995), Edelen and Warner (2001), and Hartzmark and Solomon (2022).

This paper fits into the literature on asset pricing theory in intertemporal settings and through models with heterogeneous agents. Related work includes studies by Veronesi (1999), Basak and Chabakauri (2010), Basak and Pavlova (2013), and Chabakauri (2013).[1] This literature provides tractable characterizations of equilibria with stochastic investment opportunities primarily in models where agents engage in dynamic optimization.

[1] A related strand of this literature examines the interaction of newswatchers and trend followers in the stock market (Hong and Stein, 1999; Barberis and Shleifer, 2003; Barberis, Greenwood, Jin, and Shleifer, 2015). Although dynamic investors resemble newswatchers, trend followers form beliefs about future price changes by extrapolating past price changes. This marks a sharp difference from static investors, who maintain a constant exposure to the stock market even during time periods when bonds represent more efficient investment opportunities, generating significantly different market outcomes.

The paper is organized as follows. Section 2 presents the intertemporal asset pricing theory, and Section 3 generalizes it to the cross section of stocks. Section 4 discusses robustness. Section 5 examines the empirical relevance of the theory. 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 is a risk-free bond and a set of risky stocks that distribute stochastic dividends. The risk-free bond is elastically supplied and yields the instantaneous real rate of return r. The set of risky stocks forms the equity asset class, a portfolio that distributes stochastic dividends based on the aggregate earnings of the firms underlying the individual stocks. The ex-dividend price of the equity asset class, P_t, is the sum of the ex-dividend prices of the individual stocks, with drift and diffusion denoted by μ_t and σ_t, respectively. The aggregate earnings of the firms 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 $\{\mathscr{F}_t\}$. Equation (1) 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 aggregate earnings.[2]

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.[3]

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

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 equity asset class 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.[4]

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 equity asset class, remindful of the downward sloping demand for individual securities in Harris and Gurel (1986) and Shleifer (1986). For simplicity, it is assumed that static investors reinvest the dividends

[4] For example, two funds with wealth $V_x = 100\$$ and $V_y = 200\$$ and static equity allocation $\theta_x = 0.5$ 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 funds weighted on their wealth, $\theta = 0.67$. The subsequent wealth flows into each of the funds are scaled equivalently.

distributed by equity 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. This process for wealth flows 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.[5] The wealth of static investors, V, rises in past equity market returns, dP/P, all else equal. Section 4.2 shows that this feature contributes the predictability of price volatility.

2.4 Market Clearing

The shares of the equity asset class are in fixed supply, $\overline{S}$, normalized to one without loss of generality.[6] The market clearing condition is

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

2.5 Equilibrium

The equilibrium is Walrasian and consists of a price, P, of the equity asset class such that the supply of stock shares, $\overline{S}$, is equal to their demand, $X + Q$. Dynamic investors maximize their indirect utility from consumption, given their wealth, corporate earnings, and market prices. Static investors allocate a fixed share θ of their wealth to the equity asset class, given their wealth flows. The following conditions characterize the equilibrium.

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

The first condition imposes market clearing, the second presents the Bellman equation for dynamic investors, and the third reflects the asset allocation strategy of static investors.

[5]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.

[6]The economic mechanism emphasized in this paper differs from that in standard models with stochastic supply. In those models, assets typically lose all value when it is no longer efficient to hold them.

First, consider the equilibrium 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 $p_m = \frac{1}{r^2}$.[7]

Lemma 1 describes a standard dividend discount valuation model. The result can 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 (all of the) 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. Finally, 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).

[7] 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. The appendix also reports the portfolio choice and consumption level that maximize the Hamilton-Jacobi-Bellman (HJB) 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 rises with the level of 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.

In the limit as $r \to \infty$, the dividend stream becomes worthless, prompting dynamic investors to allocate their entire wealth to the bond market and set $X = 0$, regardless of their preferences toward risk. 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* invested under static asset allocation strategies.[8]

It is important to emphasize that the above 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.

[8] In light of this observation, it is natural to consider that some agents may adjust their exposure to static asset allocation investment funds in response to new information. Section 4.1 shows that the results remain robust to this consideration.

Another insight emerging from the proposition is that the price of risky assets is influenced by the *level* 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 example, Coval and Stafford, 2007). Proposition 1 shows that the equilibrium price reflects the level 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

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

where $\mathrm{PDV}_t(D_t) = p_\gamma + p_D D_t + p_m m$ 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 Equation (8) is satisfied. In the equation, the intertemporally consistent price pressure of static investors generates the rational asset price bubble, θV_t.[9] The equity exposure of static investors, θV, affects the risky asset price 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.

The price impact of a trade is thus observed to depend on the dynamic behavior of its initiator. In the model, stock purchases by dynamic investors do not generate any price pressure. Stock purchases generates price pressure on the equity asset class only if initiated by an investor that is committed to maintaining a static asset allocation, regardless of changes in the investment opportunities. This observation offers a new perspective on the literature estimating the market-level price multiplier, namely, the price increase resulting from each dollar of equity purchases (Gabaix and Koijen, 2022).

How does the passage of time affect the relative wealth shares of dynamic and static investors? As the portfolio choice of dynamic investors is relatively more efficient, their wealth share can be expected to rise over time. Importantly, the asset classification effect remains robust to this consideration. The asset classification effect reflects the absolute level of wealth that static investors allocate to the target asset class, rather than their relative wealth share. Accordingly, in Equation (8), the rational bubble term, θV_t, depends on the level of wealth of static investors. As this wealth level increases over time, the contribution of the rational bubble term correspondingly becomes more significant.

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

Quantities held by investors characterize the equilibrium in conjunction with the price. In Appendix A, it is shown that, in equilibrium,

$$X_t(P, D, V) = \frac{\mu_t - rP_t + D_t}{r\gamma\sigma_t^2} - \frac{1-\theta}{r\gamma}Q_t, \qquad Q_t(P, V) = \theta V_t/P_t. \tag{9}$$

Dynamic investors hold a number of stock shares, X, that increases with expected returns per unit of variance and decreases with the risk-free rate. Dynamic investors' position presents a hedging term, since equilibrium prices are affected by the pressure of static investors. Static investors holds a number of stock shares, Q, that consistently fulfills their strategy. Moreover, 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.

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

As the present discounted value of fundamentals rises, the proportion of the risky asset class held by dynamic investor rises and that held by static investors falls.

The asset classification effect is relatively more important 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 influence of static investors' demand becomes a relatively more important determinant of equity asset prices.

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), $\mathrm{PDV}_t(D_t)$ is the best linear unbiased estimator of the dividend stream. Equation (10) shows that $P_t = \mathrm{PDV}_t(D_t)$ when $X_t = 1$, at which point price forecast accuracy is maximized. In general, the forecast accuracy of the price of the risky asset class for the aggregate stream of dividends rises when dynamic investors have stronger incentives to allocate resources to the equity asset class, which occurs as the expected return to risk ratio of equity assets rises. Q.E.D.

Corollary 1 emphasizes a connection between price forecast accuracy 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 equity asset class.[10]

Overall, this section has demonstrated the presence of the asset classification effect under fairly general conditions. According to this effect, the total market value of equity increases with the equity exposure of investors following static asset allocation strategies. In the time series, the asset classification effect becomes more pronounced when expected excess returns on risky assets are low and volatile.

3 The Cross Section of Stocks

The model presented thus far, which characterizes the aggregate stock market in the time series, leaves room for an important question: Which stocks appreciate the most, when the wealth of static investors rises?

In the cross section of stocks, investors can be categorized as either active stock pickers or passive index trackers. For simplicity, dynamic investors are assumed to engage in both stock picking and market timing. Static investors are instead grouped into stock pickers, who select stocks optimally but do not attempt to time the market; and index trackers, constrained from both stock picking and market timing. Figure 1 illustrates the agents.

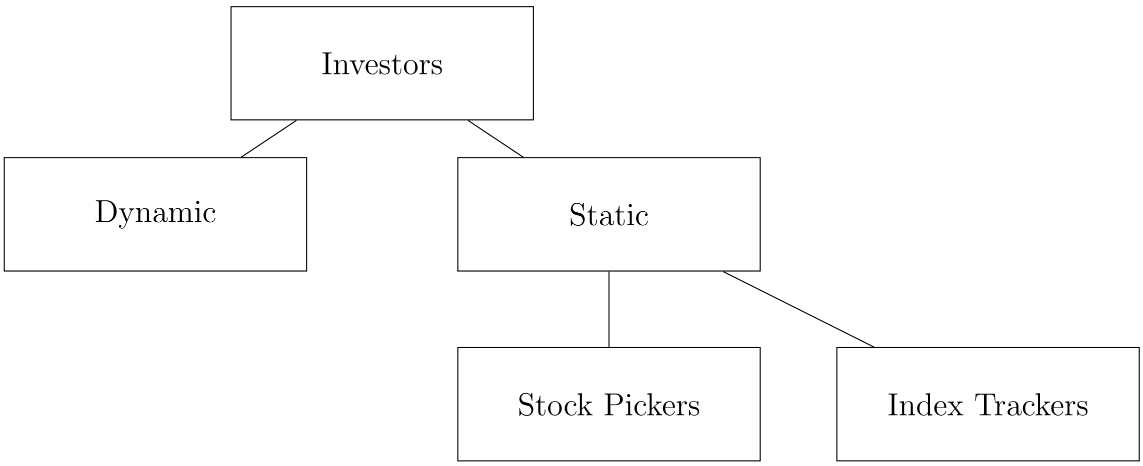

FIGURE 1: **Agents**. The figure illustrates the agents based on their portfolio constraints. Dynamic investors are unconstrained in the time series and in the cross section of stocks. Static investors hold constant equity shares over time. Within the cross section, static asset allocation stock pickers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

[10] 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.

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 real earnings of each firm are related to the real aggregate earnings in the economy in Equation (1) by the conditions $m = \sum_{i=1}^{I} m_i$ and $\omega = \sqrt{\sum_i \omega_i^2 + \sum_i \sum_{j \neq i} \omega_{ij}}$.

The shares of each stock are in fixed supply, $\overline{S}_i$, normalized to one without loss of generality. The aggregate price of the equity asset class discussed in 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

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

where the dummy variable N_i equals 1 if stock i is included in the index and 0 otherwise.

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, $V_t = V_t^A + V_t^P$.

3.3.1 Stock Pickers

The wealth of static asset allocation stock pickers, V^A, is allocated in fixed proportion, θ, to the stock market. These investors receive a fraction, π^A, of the wealth flows, F. The proportion of stock pickers' wealth invested in each stock is denoted by 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.[11] 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 $Q_{it}^A = \hat{q}_{it}\theta V_t^A / P_{it}$.

[11] This assumption does not affect the results and is intended to level the playing field between the risk preferences of dynamic investors and those of static asset allocation stock pickers, so that differences in their portfolio choices can be attributed solely to their asset allocation strategies.

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

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

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

3.4 Market Clearing

The market clearing condition for the i-th stock is

$$\underset{\downarrow}{\overset{\text{Dynamic Investors}}{}}\!\!X_{it} \quad + \quad \underset{\downarrow}{\overset{\text{Stock Pickers}}{}}\!\!Q_{it}^A \quad + \quad \underset{\downarrow}{\overset{\text{Index Trackers}}{}}\!\!Q_{it}^P \quad = \quad \overline{S}_i. \tag{16}$$

Proposition 2. Equilibrium in the Cross Section of Stocks.

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

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 extends the main result of the paper to the cross section of stocks. 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.

This proposition enables a comparison between the widely recognized index inclusion effect and the asset classification effect introduced in this paper. The index inclusion effect arises from the cross-sectional index-tracking constraint, λ_i, which imposes a limit on stock selection. The asset classification effect arises from the static asset allocation portfolio constraint, θ, which imposes a limit on market timing.

Proposition 2 demonstrates 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 concerns the relative pricing of stocks included and not included into a benchmark index, the asset classification effect concerns the pricing of the equity asset class relative to the risk-free interest rate. This is because the asset classification effect relates to the wealth that is allocated to the stock market without consideration of the relative efficiency of the bond market. Finally, it can be observed that the asset classification effect coincides with the index inclusion effect in the absence of static asset allocation stock pickers. By accounting for these investors, whose presence shapes much of equity market activity, the asset classification effect offers a generalization of the index inclusion effect and remains important even for non-index stocks.

In Appendix B, the price of the i-th stock is derived in closed form, as follows.

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

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, θV_t^P, 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 stock price drifts, volatilities, and pairwise correlations. Interestingly, 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 index stocks, which attract the investment of index trackers, and for stocks with high and stable expected excess returns, which attract the investment of stock pickers.

4 Robustness and 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 strategy investment funds may partly reflect information, and can be regarded as endogenous to the economy. For example, positive news about the stock market may attract wealth inflows into static investment funds; conversely, negative news may prompt outflows. To extend the model in this direction, consider the following specification for wealth flows.

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

where Z is a Brownian motion uncorrelated with earnings news. A value of $0 < \rho < 1$ is empirically plausible, considering that some attentive fund shareholders may time their exposure to the fund in response to earnings news, whilst other buy-and-hold fund shareholders are inattentive to earnings news. Appendix C shows that the findings of the model are robust to this extension.[12]

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

4.2 Asset Price Dynamics

The dynamics of the price of the risky asset class described in Equation (8) are given by

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

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

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

From Equation (19), it is observed that the equity holdings of static investors, Q, give rise to price amplification effects.[13]

The intuition for this effect is as follows. Price changes, dP, affect the wealth of both dynamic and static investors. 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. The numerical example reported below helps to clarify this mechanism.

Example 1. Suppose $P = \$100$, $X = Q = 0.5$, and $\theta = 0.4$. As firms report 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 fundamental news of \$20 increase in the present value of dividends, 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 equity shares, Q_t, trading against the price change. Recently, Harvey, Mazzoleni, and Melone (2025) have highlighted the quantitative importance of this pattern

[13]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.

in the data. Despite countercyclical rebalancing, it can be observed that the level of the wealth invested through static asset allocation strategies, θV_t, is procyclical. The model emphasizes that it is the *level* of wealth invested through static asset allocation strategies that influences asset prices, rather than the number of shares traded. Accordingly, the example highlights the importance of the counterfactual price that would prevail in the absence of static investors.

Several influential papers have focused their attention 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 of investors subject to portfolio constraints. While this argument carries implications for empirical research in the field, it is important to recognize 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. Appendix D further develops the analysis of asset price dynamics.

4.3 The Asset Classification Effect in the Treasury Market

The baseline model illustrates the asset classification effect in the equity market, treating the bond market as exogenous. However, the literature shows that the bond market also responds to price pressure (D'Amico and King, 2013; Vayanos and Vila, 2021).

To extend the analysis in this direction, it is possible to consider 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 of static investors, one should thus observe lower yields and bond expected returns. Appendix E extends the model in this direction.[14]

[14]Static asset allocation strategies can also increase the comovement between asset classes in excess of their common fundamentals. Previous literature on the excess comovement between stocks and bonds includes Shiller and Beltratti (1992), Connolly, Stivers, and Sun (2005), Baele, Bekaert, and Inghelbrecht (2010), David and Veronesi (2013), and Duffee (2023). This literature has largely abstract from the influence of static asset allocation strategies on asset prices.

5 Empirical Relevance

To quantify the importance of static investors in financial markets, a natural empirical proxy is given by the assets under management of professional portfolio managers, such as mutual funds (MFs) and exchange-traded funds (ETFs), operating under static asset allocation portfolio mandates. These mandates, which may be driven by agency considerations (He and Xiong, 2013), are often publicly observable.

Static asset allocation portfolio mandates constrain investors from exploiting intertemporal changes in the investment opportunity set. This point is illustrated in Figure 2. The figure builds on Gabaix and Koijen (2022), who document that MFs and ETFs maintain a constant proportion of their assets under management invested in the equity asset class, but also emphasizes the pronounced variability of the investment opportunity represented by the equity asset class. Indeed, the Sharpe ratio of the equity asset class exhibits substantial time variation, reaching a peak of 1.75 and a trough of 0.25, and reflecting sizable and stochastic changes in the investment opportunity set. These changes in the investment opportunities are, at least partly, predictable. For example, Moreira and Muir (2017) show that portfolios that take less risk when volatility is high produce large alphas. Figure 2 makes an equilibrium asset pricing model with dynamic and static investors a compelling one to study.

The model delivers a central prediction: the presence of the asset classification effect. Proposition 1, which underpins this prediction, shows that the aggregate valuation of assets within a given class rises with the wealth allocated to that asset class through static asset allocation strategies. The construction of a formal test for the presence of the asset classification effect presents a challenge, as the classification of assets within asset classes lacks exogenous variation. This makes it difficult to study the effect of the classification of the asset while keeping the fundamentals constant, as researchers do in the context of index inclusion. To overcome this challenge, the literature on aggregate price pressure exploits variation in the level of wealth allocated to an asset class. A strand of this literature presents strong evidence that unexpected aggregate cash flows into mutual funds are closely correlated with aggregate security returns (Warther, 1995; Edelen and Warner, 2001; Ben-Rephael, Kandel, and Wohl, 2011). Recent evidence by Parker, Schoar, and Sun (2023) shows that portfolio rebalancing by target date funds can increase the transmission of shocks across asset classes. Moreover, Hartzmark and Solomon (2022) show that predictable uninformed cash flows forecast aggregate market stock returns. The theory developed in this paper provides a framework to interpret these

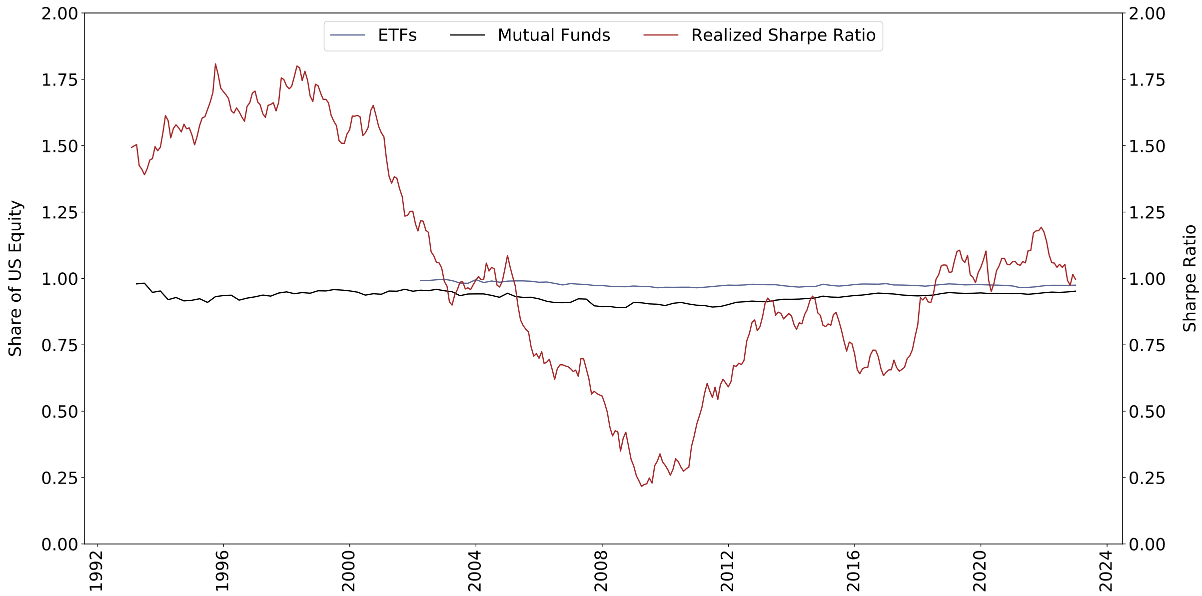

FIGURE 2: **Static Asset Allocation Strategies and the Investment Opportunity Set**. The figure shows the average U.S. Equity shares held by Mutual Funds and ETFs with weights corresponding to assets under management and the realized Sharpe ratio of the U.S. Equity asset class. Mutual Funds data from Morningstar are restricted to funds classified as U.S. Equity, Sector Equity, Allocation, and International Equity. The realized Sharpe ratio of the U.S. Equity asset class is computed as the monthly return on the value-weighted CRSP U.S. Total Market Index in excess of the risk-free rate, scaled by its one-year rolling volatility.

empirical findings.

Policymakers appear inclined to use the asset classification effect to influence financial markets. For example, on October 31, 2014, Japan's Government Pension Investment Fund (GPIF), the largest pension fund in the world, announced a major revision to its strategic asset allocation, doubling its target allocation to domestic equities from 12% to 25%. This reallocation reflected both structural demographic pressures and a broader effort to stimulate the economy under Prime Minister Shinzo Abe's administration, and was arguably unrelated to news about economic fundamentals. On the announcement day, the Japanese stock market capitalization rose by 4.5%. On the same day, the Bank of Japan announced an expansion of its Quantitative and Qualitative Easing program, complicating the attribution of market reactions. However, the magnitude of the GPIF reallocation toward domestic equities, approximately ¥17 Trillion, was likely a contributing element to observed aggregate price movements. As another example, on January 23, 2025, China Insurance Regulatory Commission asked state insurers to invest a minimum of 30% of newly added insurance premiums in local shares, while mutual funds to increase these shareholdings by 10% annually for the next three years. On the announcement day, the China Securities Index rose by 1.8%, pointing toward an appreciation of the domestic equity asset class. These examples illustrate that exogenous variation in static asset allocation investment targets can occur alongside an appreciation of the market value of assets classified within the respective asset classes.

6 Conclusion

The paper 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 discounted fundamentals. As the model shows, strategies that invest in static proportions across asset classes exert a price pressure on the securities within these asset classes. Given the persistence of this pressure, attempting to reverse its price effects would not be rational. Even investors employing dynamic asset allocations strategies can regard assets priced above their fundamental values as profitable, in the expectation to sell them at a higher price. This mechanism leads to a divergence between asset prices and their discounted cash flows. Formally, static asset allocation strategies generate a rational asset price bubble.

The paper proposes the *asset classification effect*, whereby a security's classification within an asset class has a persistent effect on its price. This effect, originating from static asset allocation strategies, offers a generalization of the index inclusion effect. Recent literature on the index inclusion effect examines its strength over time (Greenwood and Sammon, 2025) and across stocks (Pavlova and Sikorskaya, 2023). Future research could examine the asset classification effect across asset classes and time periods.

Appendix

A Proof of Proposition 1

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

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

Price drift and diffusion are, respectively,

$$\mu_t = \frac{\frac{m}{r} + \theta[rV_t(1-\theta) + Q_t D_t]}{1-\theta Q_t}, \qquad \sigma_t = \frac{\frac{\omega}{r} + \theta\pi}{1-\theta Q_t}. \tag{20}$$

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,

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

By substituting the above expressions in the HJB equation,

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

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

$$J(W,V,t) = -e^{-\delta t - r\gamma W - g(V) - \beta}, \tag{21}$$

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

$$\frac{\mu-rP+D}{r\gamma\sigma^2}-\frac{g'(V)}{r\gamma}\frac{\theta V}{P}=\frac{P-\theta V}{P},$$
$$\mu-rP+D=\frac{P-\theta V\big(1-\frac{g'(V)}{r\gamma}\big)}{P}r\gamma\sigma^2. \tag{22}$$

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 (22). After some tedious algebra,

$$\mu-rP+D=-\frac{P}{P-\theta^2 V}rp_\gamma, \tag{23}$$

which uses the relation $\frac{1}{1-\theta Q}=\frac{P}{P-\theta^2 V}$. Turning to the right-hand-side of Equation (22),

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

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 (22) 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 (20) and (23). We further know $g(V) = (1-\theta)r\gamma V + K$, thus $g'(V) = (1-\theta)r\gamma$, and

$g''(V) = 0$. After replacing $\beta = \frac{(\gamma\omega)^2}{2r} + \frac{\delta}{r} + \log(r) - 1$,

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

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 (21) 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 assets.

Q.E.D.

B Proof of Proposition 2

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

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

There is aggregate price pressure, 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

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

Thereby, the 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.

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

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

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

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.

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

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 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

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

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.

D Asset Price Dynamics

Asset price dynamics can be obtained by replacing the dynamics of dividends, dD_t, and those of the wealth dynamics of static investors, dV_t, into Equation (19).

$$dP_t = A_t\left(\frac{m}{r} + \theta\big[rV_t(1-\theta) + Q_tD_t\big]\right)dt + A_t\left(\frac{\omega}{r}dB_t + \theta\pi dF_t\right), \tag{24}$$

where $A_t = 1/(1-\theta Q_t)$ captures the amplification effect associated with static asset allocation strategies. The strength of such effect rises as static investors own a larger proportion of the stock market, Q_t. As the investors composition is public information, such amplification is predictable.

In equilibrium, stock price dynamics result from two distinct processes, representing economic fundamentals and the importance of static investors. Accordingly, the price drift reflects predictable earnings, $\frac{m}{r}$, and predictable price pressure from static investors, $\theta[rV_t(1-\theta)+Q_tD_t]$, resulting from their bond investments as well as from their dividend reinvestments. The volatility of price changes refeclts both the volatility of fundamentals, $\frac{\omega}{r}$, as well as that of wealth flows, a proportion $\theta\pi$ of which may affect asset prices introducing non-fundamental volatility. This mechanism is remindful of Ben-David, Franzoni, and Moussawi (2018).

These consideration motivate a time series analysis of volatility of market returns with a structural interpretation of equity ownership data. Daily S&P 500 returns data are retrieved from Bloomberg. Quarterly U.S. stock market holdings data are retrieved from the Flow of Funds statistics and illustrated in Figure A.1. The importance of professional asset managers 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.

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] As

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

shown below, the model relates the returns $\mathtt{r}_{\mathtt{d,q}}$ realized on day $\mathtt{d}$ in quarter $\mathtt{q}$ 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 $\mathtt{b}$.

$$\begin{aligned} \mathtt{r}_{\mathtt{d,q}} &= \mathtt{m} + \sqrt{\mathtt{l}_{\mathtt{q}}\mathtt{g}_{\mathtt{d,q}}}\mathtt{e}_{\mathtt{d,q}}, \\ \mathtt{l}_{\mathtt{q}} &= \mathtt{n} + \mathtt{c}\sum_{\mathtt{k}=1}^{\mathtt{K}} \mathtt{f}_{\mathtt{k}}(\mathtt{w}_1, \mathtt{w}_2)\text{Static Share}_{\mathtt{q-k}}, \\ \mathtt{g}_{\mathtt{d,q}} &= (1 - \mathtt{a} - \mathtt{b}) + \mathtt{a}\frac{(\mathtt{r}_{\mathtt{d-1,q}} - \mathtt{m})^2}{\mathtt{l}_{\mathtt{q}}} + \mathtt{b}\mathtt{g}_{\mathtt{d-1,q}}. \end{aligned} \tag{25}$$

The model in Equation (25) enables the same news to have different effects depending 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 $\text{Static Share}_{\mathtt{q}}$. The model suggests that the response of returns to news should be amplified when static investors hold a larger proportion of the stock market. This effect can be quantified by the coefficient $\mathtt{c}$, which is expected to be positive and statistically significant.

Table A.1 presents the coefficient 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.

E Aggregate Price Pressure in the Treasury Market

The static asset allocation strategy requires investors to invest a fixed proportion of their wealth in the bond market, regardless of risk and return considerations. Greenwood and Vayanos (2014) suggest that a shock to the demand for bonds should impact the yields of all bonds in the opposite direction as the shock. Moreover, a shock to the demand factor should affect the instantaneous expected returns of all bonds in the opposite direction as the shock. After an exogenous increase to the wealth invested under static asset allocation strategies, one should thus observe lower yields and bond expected returns.

Recent empirical research has investigated aggregate price pressure in the context of stock market dividend payout days. Hartzmark and Solomon (2022) document that days in the top quintile of dividend payments are associated with higher stock 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 MFs and ETFs have become a larger component of equity holdings. With a model with static and dynamic investors in mind, it is natural to extend such analysis to investigate whether stock market dividend payout days generate effects on the Treasury market.

Figure A.2 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 data reveal a clear pattern of large economic significance. Days with large dividend payment amounts feature large returns on the stock market (Panel A), low Treasury term premia (Panel B), and low expected returns on 10-year Treasury bonds (Panel C). This result is consistent with the aggregate price pressure of investors following static asset allocation strategies.

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

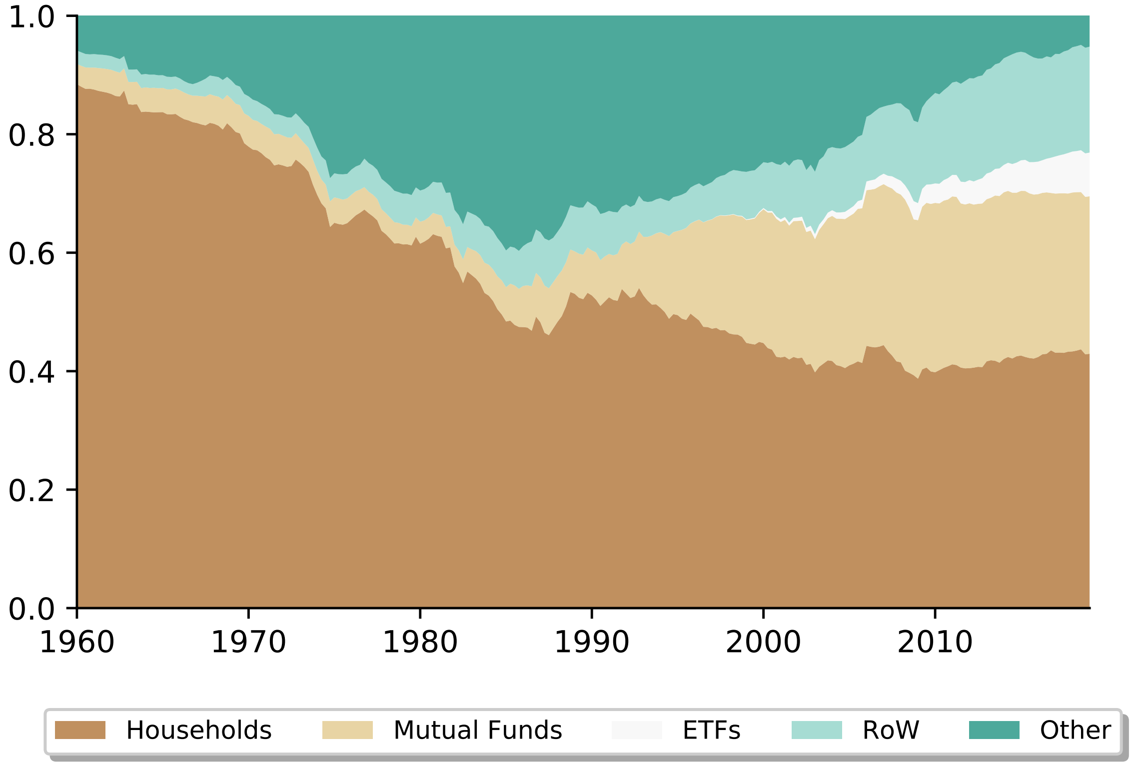

FIGURE A.1: **U.S. Equity Ownership**. The figure displays the composition of investors in U.S. corporate equities, based on Financial Accounts data published by the Federal Reserve. ETFs denotes exchange-traded funds, while RoW refers to the rest of the world.

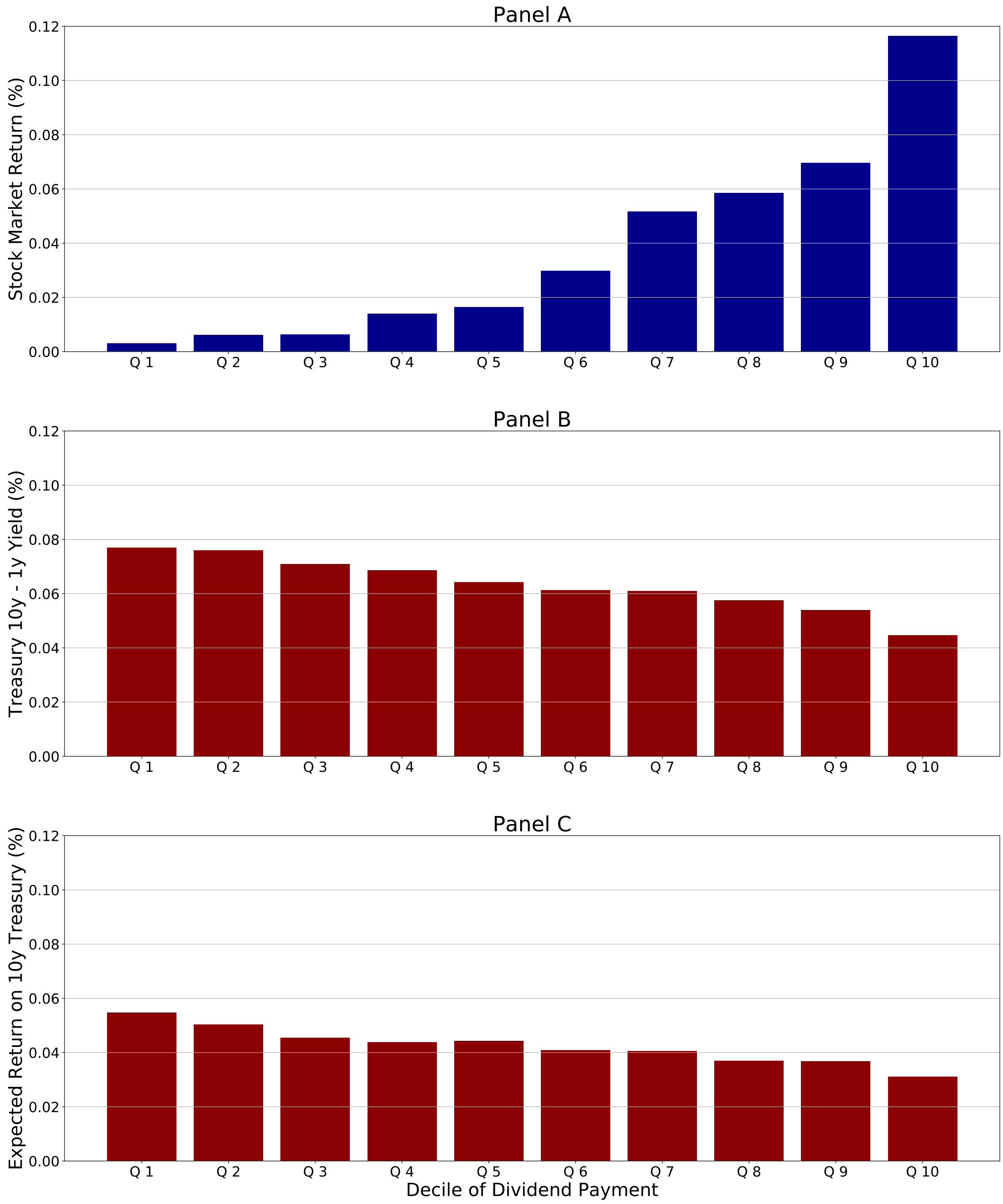

FIGURE A.2: **Wealth Effects in Equity and Treasury Markets**. Trading days are grouped into deciles by dividend payment amount, which are reported on the x-axis. Panel A: the y-axis shows the value-weighted market return, averaged within each decile. Panel B: the y-axis shows the return on the 10-year 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).

Table A.1: **Parameter Estimates of GARCH-MIDAS with Investor 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:

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

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 Investors$_{\mathtt{q}}$ is the proportion of the stock market held by MFs and ETFs, and the remaining terms are parameters.