Asset Pricing with Dynamic and Static Investors

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ABSTRACT

The economy features dynamic investors, who condition their asset allocation on news, and static investors, who allocate wealth across asset classes in preset proportions. This paper models how their interaction determines stock prices. Because static investors consistently follow their asset allocation strategy over time, their wealth generates current and prospective demand pressure on stocks. Dynamic investors are unconstrained, yet they cannot profitably arbitrage away this demand pressure, as stock prices are rationally expected to remain elevated by static investors' support. In equilibrium, stock market valuation reflects static investors' level of wealth, over and above wealth flows, dividends, and discount rates.

JEL classification: G11, G12, G23.

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1 Introduction

What determines the level of stock prices? Standard asset pricing theories explain stock prices as the outcome of agents' dynamic optimization—e.g., by households (Merton, 1973), firms (Cochrane, 1991), or intermediaries (He and Krishnamurthy, 2013). In the traditional view, stocks are priced at the present discounted value of their expected future dividends by agents engaging in dynamic asset allocation strategies who control their policies in response to news. Gabaix and Koijen (2023) offer a new perspective, by observing that investors adopting static asset allocation strategies keep their capital allocation across asset classes close to target weights that exhibit little to no variation in response to news. In this more recent view, wealth flows to the stock market generate price pressure due to the absence of unconstrained investors engaging in dynamic asset allocation available to accommodate the resulting demand for stocks.

Financial markets include investors who adopt dynamic asset allocation strategies as well as investors who adhere to static asset allocation strategies.[1] This coexistence suggests that, while both perspectives discussed above capture important forces, neither of the two is complete in isolation. This paper integrates them by developing and solving in closed form an intertemporal capital asset pricing model with two groups of agents. *Dynamic Investors*, representing the sector of financially sophisticated households and hedge funds, optimize expected utility from consumption by adjusting their asset allocation upon the arrival of news, as in Merton (1973). *Static Investors*, representing the sector of balanced mutual funds and exchange-traded funds (ETFs), are professionally managed institutions that adhere to a static asset allocation strategy, as in Gabaix and Koijen (2023). Consistent with their role as institutional investors, static investors receive stochastic capital flows that contain a component unrelated to news.

The key finding of this paper is that the equilibrium valuation of the stock market exceeds the risk-adjusted present value of its dividend stream by a term that increases linearly in the level of wealth managed by static investors. I refer to this term, which arises because static investors' strategy compels them to hold assets classified as equities, as the *Asset Classification Effect*. The asset classification effect can explain (at least partly) the evidence on the aggregate effect of wealth flows into mutual funds on stock prices first documented by Warther (1995) and Edelen and Warner (2001). At the same time, it points to wealth *flows* as part of a broader quantity that impacts asset prices: the *level* of wealth invested under static asset allocation strategies, which reflects wealth flows, equity allocation targets, and dividend payments. This perspective is consistent with evidence of price pressure from wealth reallocation across funds with diverse equity targets (Da et al., 2018) and from dividend payments (Hartzmark and Solomon, 2025).

[1] Dynamic asset allocation strategies are observed among hedge funds (Fung and Hsieh, 1997), mutual funds that engage in market timing (Kacperczyk et al., 2014), and households that are wealthy (Giglio et al., 2021) and have high cognitive ability (Grinblatt et al., 2012). Static asset allocation strategies are characteristic of, though not universal among, institutional investors such as pension funds (Andonov and Rauh, 2022) and balanced mutual funds (Dahlquist and Ibert, 2024), as frequently formalized in their prospectuses. They are also widely recommended by financial advisors to retail investors (Canner et al., 1997).

A quantitative assessment of the model treats mutual funds and ETFs that maintain stable equity allocations over time as the empirical counterpart of static investors. This assessment highlights a first-order distinction between the level of wealth managed by these investors and the net wealth flows they receive. The former series exhibits an upward trend, reaching around $7.9 trillion in 2024. The latter, computed following Lou (2012), is stationary and equals about $87 billion in 2024. In other words, the model identifies as a potentially important source of persistent price pressure the level of wealth invested in stocks under static asset allocation strategies, a quantity significantly larger and more persistent than the wealth flows emphasized by the previous literature.

The presence of static investors is the sole ingredient that sets the model apart from standard theories based on intertemporal optimization in frictionless capital markets. Static investors are best interpreted as institutional investors following a static asset allocation strategy. Over time, as wealth inflows to these institutional investors alternate with wealth outflows, static investors consistently operate under their asset allocation strategy, allowing at most limited deviations from asset allocation targets in response to news. Casually speaking, static investors commit a stable share of the capital they manage to a tree, regardless of the fruits it bears. This simple ingredient leads to rich equilibrium implications, because it makes stock prices depend directly on the equity exposure of static investors.

The model demonstrates that the price pressure exerted by static investors is compatible with the workings of dynamic investors who face neither borrowing limits nor short-sale constraints. The intuition runs as follows. As dividends are governed by an exogenous stochastic process, an increase in demand for stocks from static investors must be absorbed either by higher market prices or by dynamic investors establishing a short position in anticipation that stock prices will eventually converge to the risk-adjusted present value of the stocks' dividend stream.

Why do dynamic investors not find it profitable to take a short position to accommodate the demand for stocks from static investors and prevent that demand from creating price pressure? The reason is that the demand from static investors is not a temporary deviation expected to be corrected. In fact, static investors continue to adhere to their strategy across states of the economy and over time. Because their asset allocation remains largely unchanged across states, static investors continue to demand equity assets whether dividend news is good or bad. And because their strategy is to maintain a given asset allocation over time, static investors' demand pressure is expected to support stock prices in the present and in the future alike. Dynamic investors are unconstrained, but short-selling against demand pressure that is not expected to dissipate does not yield any arbitrage profits. Stock prices remain elevated, under the rational expectation of high prices going forward. This rational stock price deviation from the present value of the dividend stream is reminiscent of Tirole (1985), except that the price pressure is not created by elements that are extraneous to the economy, i.e., sunspots. Instead, the price

pressure examined in this paper is created by static investors, can be measured using portfolio holdings data, and is economically interpretable.

After examining the aggregate stock market valuation, three interrelated questions remain. First, how should the portfolio choice of dynamic investors account for the presence of static investors in financial markets? The analysis reveals that the presence of static investors induces a tilt in the optimal portfolio of dynamic investors. Beyond the myopic component that reflects the contemporaneous trade-off between risk and return, dynamic investors' optimal portfolio also contains an intertemporal hedging component that depends on the number of equity shares held by static investors. Intuitively, when static investors become larger owners of the stock market, stock prices become more driven by their wealth than by dividends. This makes stocks less attractive as vehicles to finance future consumption, because high ownership by static investors tends to coincide with lower expected returns. Hence, as the static investors' ownership share of the stock market rises, dynamic investors tilt their portfolios away from equity assets. Consistent with this mechanism, predictive regressions show that high stock market ownership by the empirical counterpart of static investors forecasts lower aggregate stock market returns.

Second, when in the time series does capital invested under static asset allocation strategies exert greater price pressure? The model reveals that static investors' capital becomes relatively more important for equilibrium stock prices when expected excess stock returns are low, at which point dynamic investors shift their portfolio toward the risk-free asset. In such cases, static investors' inelastic demand for equity assets sustains the stock market valuation, and stock prices increasingly reflect static investors' equity exposure rather than dividend streams. The same logic applies to negative earnings surprises, which lead dynamic investors to reduce their stock market exposure. Generally speaking, static investors' wealth is thus more important for equilibrium stock prices in bad times than it is in good times. Consistent with this view, the stock market ownership share of the empirical counterpart of static investors is negatively correlated with risk-adjusted excess stock market returns.

Third, which security prices in the cross-section are most influenced by the capital invested under static asset allocation strategies? To address this question, one has to examine not only static investors' asset allocation, but also their stock selection. To parsimoniously extend the model in this direction, static investors are divided into two groups: *Index Trackers* and *Stock Pickers*. Index trackers following static asset allocation strategies (such as passive balanced mutual funds and ETFs) continuously track the performance of an index composed of a subset of stocks. Stock pickers following static asset allocation strategies (such as active balanced mutual funds and ETFs) optimally select the mix of stocks in their portfolio at each point in time. The model shows that even stock pickers, despite their optimal cross-sectional selection of stocks, exert aggregate price pressure on the equity asset class, by maintaining their exposure to the stock market close to a static asset allocation target.

In the cross-section, the equilibrium price of each stock exceeds the risk-adjusted present discounted value of its dividend stream by a term that increases linearly in the stock's weight in the portfolio of investors following static asset allocation strategies, whether stock pickers or index trackers. This result points to two sources of price pressure on individual stocks. First, the *index inclusion* of a stock influences its price, as it makes that stock part of the asset demand of index trackers. Accordingly, the price pressure on index stocks rises with the level of wealth managed by index trackers, as more capital is passively deployed to index stocks. Second, the *asset classification* of a stock also influences its price, as it makes that stock part of the asset demand of static investors with target exposure to the equity asset class. Accordingly, the price pressure on equity assets rises with the level of wealth managed by static investors, as more capital is deployed to the stock market. The economic intuition is transparent: much like cross-sectional constraints due to index-tracking policies affect the prices of stocks included in an index, constraints imposed by static asset allocation strategies affect the prices of the securities classified into target asset classes. Consistent with this prediction, cross-sectional regressions show that stocks more heavily held by the empirical counterpart of static investors trade at lower dividend yields. Overall, this analysis sheds some light on the relationship between the price pressure at the individual stock level (Harris and Gurel, 1986; Shleifer, 1986) and at the asset class level, a relationship that appears to have been largely neglected in the literature.

The effect of demand forces on the aggregate valuation of the stock market was first explored by Warther (1995) and Edelen and Warner (2001). Recent empirical studies in this field include Da et al. (2018), Parker et al. (2023), and Hartzmark and Solomon (2025). Gabaix and Koijen (2023) show that wealth flows to the stock market generate significant price impacts, attributing this finding to a lack of unconstrained investors engaging in dynamic optimization. Building on their paper, a growing literature studies the macro-elasticity of financial markets, examining the price impact of wealth flows. This paper makes four contributions to this literature. First, it proposes a theory in which the stock market valuation reflects the level of wealth invested in stocks under static asset allocation strategies, over and above wealth flows, dividends, and discount rates. Second, it offers some guidance on how to approach intertemporal portfolio optimization in the presence of price pressure from static asset allocation strategies. Third, this paper suggests that wealth flows to the stock market should not be treated symmetrically. A flow into the stock market from dynamic investors reacting to earnings news likely reflects relevant information, so that the associated price impact points to efficient markets, rather than inelastic markets. Instead, a flow into the stock market from static investors likely does not reflect news about earnings, so that the associated price impact points to inelastic markets. This heterogeneity suggests that identifying the broader intertemporal strategy behind an investment flow may sharpen the interpretation of its price impact. Fourth, this paper presents a novel asset pricing mechanism that shows that price pressure from static asset allocation strategies is

compatible with the workings of unconstrained investors engaging in dynamic optimization.

By recognizing the importance of institutional investors' demand for equity assets, this paper ties in well with the literature on the macrostructure of financial markets, surveyed by Haddad and Muir (2025). Koijen and Yogo (2019) helped draw considerable attention to investment policies by estimating asset demand systems. Although the demand system approach to asset pricing has yielded fundamental insights, it has also raised points of debate. For instance, Fuchs et al. (2023) caution against interpreting estimated demand elasticities as structural parameters, van Binsbergen et al. (2025) point out that the path of future trading prices may be an omitted asset characteristic, and He et al. (2025) emphasize that demand shocks can violate the exclusion restriction in dynamic economies. By considering investment strategies, which specify a plan of action at each point in time, this paper incorporates key insights from the literature on asset demand systems while remaining robust to the aforementioned considerations.

Related literature on asset pricing theory in intertemporal settings with heterogeneous agents includes Basak and Chabakauri (2010), Chabakauri (2013), and Kimball et al. (2020). This literature provides tractable characterizations of intertemporal equilibria primarily in models where all agents engage in dynamic optimization.[2] In particular, the dynamic investors' problem is closely related to that in Veronesi (1999), where investors learn about dividend growth. Here, dynamic investors interact with investors who follow static asset allocation strategies. Basak and Cuoco (1998) consider a model with restricted stock market participation. In this paper, some agents forego dynamic portfolio choice, rather than stock market participation, by delegating capital to institutional investors following static asset allocation strategies. In Hugonnier (2012), restrictions on one group of investors' portfolio choices can generate a rational bubble. The remaining investors can freely choose their portfolio composition, but face solvency requirements that limit their ability to exploit the resulting mispricing. In this paper, static investors' continuing demand supports current and prospective prices, so dynamic investors cannot profitably arbitrage away the resulting price pressure, even though they are unconstrained. Basak and Pavlova (2013) also examine asset prices and institutional investors. However, their analysis centers on institutions that care about their performance relative to a benchmark index, while this paper studies static capital allocation across asset classes and its implications for the aggregate stock market valuation.

Notwithstanding the importance of the static asset allocation strategy, theoretical exploration of its effects in capital markets remains limited. Chien et al. (2011) and Chien et al. (2012) show that heterogeneous asset allocation strategies help to match asset prices and the distribution of household wealth. Their frameworks specify a complete menu of one-period Arrow-Debreu

[2] A related strand of this literature studies the interaction of newswatchers and trend followers in financial markets (Hong and Stein, 1999; Barberis and Shleifer, 2003; Barberis et al., 2015). Although dynamic investors resemble newswatchers, trend followers form beliefs about future price changes by extrapolating past price changes. In sharp contrast, static investors maintain a pre-specified exposure to the stock market even during time periods when bonds represent more efficient investment opportunities, generating entirely different market outcomes.

securities, which precludes price pressure from lasting beyond one period, in contrast to the mechanism studied in this paper. Duarte et al. (2025) study the stock market elasticity when investors follow heterogeneous investment strategies and show that equilibrium interest rate adjustments and arbitrage forces prevent transitory wealth flows from generating price pressure, absent frictions such as leverage constraints. Their results are derived as perturbations around a benchmark economy, which are useful for examining state-dependent responses to flows, but abstract from the possibility that stock prices persistently exceed the risk-adjusted present value of their dividend streams. This paper does not rule out such a possibility by assumption, and finds that the level of wealth invested under static asset allocation strategies generates an economically large and persistent (asset classification) effect on both the aggregate valuation of the stock market and the cross-section of stock prices. To the best of my knowledge, this paper is the first to show that price pressure on stocks exerted by institutional investors operating under static asset allocation strategies is compatible with the workings of investors engaging in dynamic optimization in frictionless capital markets.

I examine the robustness of my theory to various considerations without qualitative changes to my findings. I consider correlation between wealth flows and earnings news, allow static investors to have flexible investment targets (Buffa et al., 2022), examine whether the results remain valid under general preferences for dynamic investors, and discuss survival of agents (Kogan et al., 2006). Taken together, these exercises suggest that my findings can be attributed to the interaction between dynamic and static investors, rather than specific model assumptions. The remainder of this paper is organized as follows. Section 2 presents the model and derives the equilibrium stock market valuation. Section 3 solves for the equilibrium in the cross-section of stocks. Section 4 examines the empirical relevance of the model. Section 5 concludes.

2 The Model

Time is continuous and goes from zero to infinity. Investors form rational expectations using a common information set, and are grouped into two categories. Dynamic investors optimize their asset allocation in response to news. Static investors maintain a predetermined asset allocation, without regard to the revelation of information. The environment is otherwise standard.

2.1 Assets

The economy features a risk-free bond and a set of stocks that distribute stochastic dividends. The bond is elastically supplied and yields the constant risk-free real rate of return r.[3] The set of stocks forms the equity asset class. The equity asset class valuation, P_t, is defined as the sum of the market capitalizations of the individual stocks. Its drift and diffusion are denoted by μ_t and σ_t, respectively. The aggregate earnings of the listed firms, denoted by E_t and expressed in

[3]While one could consider a stochastic risk-free rate, as in Merton (1973), the economic mechanism identified here would remain unchanged.

real terms, follow a stochastic differential equation with drift m and diffusion ω,

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

B_t is a Brownian motion on a probability space with filtration $\{\mathcal{F}_t\}$. Equation (1) is consistent with linear growth in real earnings. The aggregate dividend rate, net of rights issues, is proportional to the aggregate earnings, $D_t = aE_t$. The payout ratio is normalized to $a = 1$.[4]

2.2 Dynamic Investors

Dynamic investors have the instantaneous utility function $U(c_t) = -\exp(-\gamma c_t)$, where c_t denotes consumption and γ is a risk-aversion parameter, and discount future utility at rate δ. Their policies change continuously as news reaches the market, in the style of Merton (1973). Specifically, dynamic investors control their consumption and portfolio to maximize utility from consumption over an infinite time horizon, subject to their dynamic budget constraint and transversality condition. They are not subject to any leverage or short-selling constraints. Their derived utility from consumption is

$$J(W_t, V_t, t) \equiv \max_{\{c_s, X_s\}} \quad \mathbb{E}_t\left[\int_t^\infty e^{-\delta s} U(c_s)\, ds\right], \tag{2}$$

$$\text{s.t.} \quad dW_t = (rW_t - c_t)dt + X_t dY_t, \qquad \lim_{h\to\infty} \mathbb{E}_t\Big[J(W_{t+h}, V_{t+h}, t+h)\Big] = 0. \tag{3}$$

In the above expressions, W_t denotes dynamic investors' wealth and V_t static investors' wealth. Moreover, $dY_t = (D_t - rP_t)dt + dP_t$ is the excess dollar payoff on the market portfolio, financed at the risk-free rate, and X_t is dynamic investors' ownership share of the stock market. The dynamic budget constraint describes the accumulation of wealth through the risk-free bond and exposure to the excess return on the stock market, net of consumption. The transversality condition ensures that the value function does not diverge by requiring that dynamic investors plan to eventually consume their wealth. This optimization program is standard (see, e.g., Veronesi, 1999). Interestingly, however, dynamic investors interact with static investors, described below.

2.3 Static Investors

Static investors represent the sector of institutional investors that operate under static asset allocation strategies. They continuously rebalance their portfolios to maintain target exposures across asset classes, without regard to current or prospective market prices. For expositional simplicity, those institutional investors are aggregated into a representative fund whose wealth,

[4] Rights issues, which reduce the value of the shares outstanding without affecting their supply to the public, can account for negative dividends.

V_t, is allocated in a constant proportion, θ, to the stock market.[5] It is assumed that $\theta \in [0, 1)$, as pure equity funds such as equity ETFs invest primarily in stocks, while balanced mutual funds only allocate a fraction of their wealth to stocks. Internet Appendix A allows for flexibility in the response of the target equity allocation to the revelation of news.

Static investors operate as going concerns that deploy their capital under management in adherence to static asset allocation strategies. Static investors are thus characterized by their asset allocation and wealth under management. Their asset allocation strategy determines their stock market ownership share, Q_t, where

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

The wealth under management of static investors is driven by price revaluations and capital flows. Thus, assuming for simplicity that dividends are reinvested, it evolves as follows.

$$dV_t = V_t\big[(1-\theta)r dt + \theta(dP_t + D_t dt)/P_t\big] + \pi dF_t, \tag{5}$$

where π is a loading parameter and F_t is a Brownian motion adapted to $\{\mathscr{F}_t\}$ that drives wealth flows to static investors net of share redemptions.[6] Wealth flows to static investors are assumed to be uncorrelated with earnings news, an assumption relaxed in Internet Appendix B. Internet Appendix C further enriches the specification by allowing for a drift term in the process for wealth flows. The modelling of static investors described above departs from the intertemporal optimization paradigm in two respects:

1. Static investors do not choose consumption or asset allocation. Instead, static investors professionally manage retail investors' wealth according to preset allocation mandates. Retail investors contribute capital to the funds and withdraw it to finance consumption. These contributions and withdrawals are summarized by the net wealth flows πdF_t.

2. No transversality condition is imposed on static investors' assets under management. Individual retail investors invest in static funds for a limited time, but they alternate with other retail investors. Static investors are assumed to operate indefinitely, much like firms are assumed to generate earnings indefinitely.

A micro-foundation for this economy is provided in Appendix A. Static investors are interpreted as institutional investors acting on behalf of overlapping generations of inertial retail agents. Retail agents inertially delegate capital to static investors for diverse periods of time,

[5] For instance, two funds with wealth $V_x = \$100$ and $V_y = \$200$ and equity targets $\theta_x = 0.5$ and $\theta_y = 0.75$ aggregate into a representative fund with wealth $V = \$300$ that allocates to equities the wealth-weighted average of the two targets, $\theta = 0.67$.

[6] Following extreme wealth outflows, V_t could potentially turn negative. Its dynamics could be disciplined by a term ηdL, where η is the speed of reflection and L the local time of V_t at zero. Empirically, such outflows have negligible probability. I thus abstract from this consideration.

during which their capital is deployed according to static investors' asset allocation strategy. The overlapping-generations setting generates the wealth-flow process, πdF_t, capturing the aggregate capital flows faced by institutional investors operating under static asset allocation strategies observed in the data. Stepping out of the micro-foundation, the analysis remains confined to static investors, as they directly trade in capital markets on behalf of retail agents.

Ultimately, regardless of the source of their assets under management, static investors deploy capital according to preset asset allocation targets. Equations (4) and (5) connect the model directly to observable features of mutual funds and ETFs following static allocation strategies: their assets under management, asset allocations, and net flows.

2.4 Market Clearing

The stock market portfolio is in fixed supply, S, normalized to one without loss of generality.[7] The market clearing condition is

$$X_t + Q_t = S. \tag{6}$$

2.5 Equilibrium

The equilibrium consists of a market valuation of the equity asset class such that dynamic and static investors' holdings of the market portfolio sum to its unit supply. Dynamic investors maximize their indirect utility from consumption. Static investors allocate a fixed share of their wealth to the equity asset class. Thus, the equilibrium is characterized by three equalities:

$$X_t + Q_t = S, \qquad 0 = \max_{\{c_t, X_t\}} \left\{ e^{-\delta t} U(c_t) + \frac{\mathbb{E}_t[dJ(W_t, V_t, t)]}{dt} \right\}, \qquad Q_t = \theta V_t / P_t. \tag{7}$$

The first equality imposes market clearing. The second solves the Hamilton-Jacobi-Bellman (HJB) equation for dynamic investors. The third is the static investors' asset allocation strategy.

2.6 Equilibrium without Static Investors

The analysis begins by deriving a benchmark equilibrium in the absence of static investors, by setting their target equity exposure $\theta = 0$. Throughout the paper, $\mathbb{E}_t^*$ denotes conditional expectations taken with respect to the probability measure adjusted for the dynamic investors' preferences toward risk. Optimal policies are instead denoted with a star superscript; e.g., $X_t^\star$.

Lemma 1. Equilibrium without Static Investors.

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

[7] Dynamic investors absorb the residual supply $S - Q_t$, making this paper similar in spirit to models with exogenous stochastic asset residual supply, such as Campbell and Kyle (1993) and Wang (1993). What sets this paper apart is that residual supply follows from static investors' allocation rule and intertemporal wealth accumulation, in Equations (4) and (5), and therefore responds endogenously to market prices.

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

Substituting the process for dividends into dynamic investors' HJB yields the representation

$$P_t = \text{PDV}(D_t). \tag{8}$$

$\text{PDV}(D_t) = p_g + p_D D_t + p_m m$ denotes the present discounted value of the expected aggregate dividend stream, net of the risk adjustment required by dynamic investors for the exposure of the equity asset class to earnings risk. Moreover, $p_g = -\frac{\gamma\omega^2}{r^2}$, $p_D = \frac{1}{r}$, and $p_m = \frac{1}{r^2}$.[8] Lemma 1 describes a standard dividend discount valuation model. This equilibrium can alternatively be obtained by iterating forward the no-arbitrage restriction in dynamic market environments, $P_t = e^{-rdt}\mathbb{E}_t^*[P_{t+dt} + D_t dt]$, and imposing the following transversality condition:

$$\lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*[P_{t+h}] = 0. \tag{9}$$

Absent the transversality condition in Equation (9), the stock market valuation would exceed its discounted dividend stream, leading to a rational bubble. A rational bubble is defined here as a difference between an asset's price and the risk-adjusted present value of its expected cash flows that does not constitute an arbitrage opportunity. This definition follows the literature on rational expectations in present-value models (Tirole, 1985; Froot and Obstfeld, 1991; Santos and Woodford, 1997). It does not require that the asset's cash flows be replicable, but that the asset bears the same yield as alternative assets. Indeed, when the asset's risk-adjusted expected return equals that on alternative assets, the asset price deviation from its fundamental is merited (Stiglitz, 1990). A rational asset price bubble, if present, impacts both the current level of the asset price and its risk-adjusted expected future value equally. Tirole (1982) argues that rational bubbles are not present when agents optimize their actions dynamically. Lemma 1 is consistent with this view, because all of the agents are dynamic investors, stock market valuation equals the discounted aggregate dividend stream, and the transversality condition is respected. Namely,

$$\lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*[P_{t+h}] = \lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*[\text{PDV}(D_{t+h})] = 0. \tag{10}$$

2.7 Equilibrium with Dynamic and Static Investors

Static investors induce a stark departure from the benchmark equilibrium in Section 2.6, as they *consistently* deviate from dynamic optimization of their asset allocation. With static investors, Lemma 1 does not constitute an equilibrium, because that pricing function cannot clear the

[8] Throughout the paper, it is assumed that the risk correction is not too large, so that equilibrium prices remain strictly positive after the additive risk adjustment. An analogous parametric restriction is maintained in Veronesi (1999).

market of the demand from static investors for all possible realizations of the risk factors. Proposition 1 below examines the equilibrium with dynamic and static investors, demonstrating that static investors impact the stock market valuation through an asset classification effect.

Proposition 1. Equilibrium with Dynamic and Static Investors.

$$P_t = \underbrace{\text{PDV}(D_t)}_{Fundamentals} + \underbrace{p_f + \theta V_t}_{Asset\ Classification\ Effect} \tag{11}$$

where $p_f = -\gamma\theta\pi^2$ is the risk adjustment induced by stochastic wealth flows to equity assets.

Proof. Appendix B presents the proof of this statement and the associated optimal portfolio and consumption rules that maximize the HJB equation for dynamic investors. To complement the equilibrium analysis, Appendix C derives the corresponding Stochastic Discount Factor (SDF).

Proposition 1 shows that the aggregate stock market valuation reflects its *Fundamentals*, the risk-adjusted present value of its expected cash flows, given the discount rates required by dynamic investors—the marginal agents, whose optimality conditions determine asset prices. Above and beyond its fundamentals, the stock market valuation reflects the presence of static investors through the *Asset Classification Effect*, which operates on stock prices through two distinct channels: (i) the flow risk adjustment, p_f, induced by the exposure of stock prices to stochastic wealth flows to static investors; (ii) the equity exposure of static investors, θV_t, which puts upward pressure on stock prices. Notably, the presence of static investors leaves the risk-adjusted present discounted value of the dividend stream entirely unaffected.

As an illustration of the asset classification effect, consider a comparative statics exercise. Suppose that bonds are temporarily expected to outperform stocks. Dynamic investors then want to take a short position in stocks and invest in the bond market. Absent static investors, stock prices would have to fall until expected excess returns are sufficiently positive for dynamic investors to absorb the supply of shares. This constitutes a serious limitation of the dividend discount model in Lemma 1—bonds *are* sometimes expected to outperform stocks. For instance, Gómez-Cram (2022) documents that stock returns are predictably lower than the risk-free rate for several months after the onset of recessions. How can stocks have positive prices, when the risk-free asset is expected to outperform them and investors are risk-averse? The asset classification effect offers a way forward: over and above the discounted dividend stream, stocks price the level of wealth invested in the equity asset class under static capital allocation strategies.

There is considerable evidence that wealth flows to investment funds impact stock prices (e.g., Coval and Stafford, 2007). The asset classification effect is consistent with this evidence, but embeds wealth *flows*, dF_t, within a broader state variable: the *level* of wealth managed by static investors, V_t, whose evolution is described by Equation (5). Hence, it suggests that

price pressure may be much larger than previously thought. This perspective also speaks to the evidence of price pressure originating from wealth reallocation between funds with different asset allocation targets (Da et al., 2018), dividend distributions (Hartzmark and Solomon, 2025) and portfolio rebalancing (Harvey et al., 2025), as discussed in Appendix E. The next two remarks characterize important properties of the equilibrium pricing function.

Remark 1. A Martingale Property for the Asset Classification Effect. In financial markets free of arbitrage opportunities, the risk-adjusted expected return on stocks coincides with the rate of return on the risk-free asset. Thus, under the risk-adjusted measure, the conditional expectation of the evolution of static investors' wealth under management in Equation (5) is

$$\mathbb{E}_t^*[dV_t] = rV_t dt + \mathbb{E}_t^*[\pi dF_t]. \tag{12}$$

Moreover, static investors' equity exposure, θ, is known in advance and constant over time. These observations can be used to show that, for every positive time horizon h,

$$p_f + \theta V_t = e^{-rh}\mathbb{E}_t^*[p_f + \theta V_{t+h}]. \tag{13}$$

Thus, the asset classification effect is a discounted martingale under the risk-adjusted measure. As a consequence, it impacts the contemporaneous stock market valuation and its risk-adjusted expected future valuation equally.

Proof. See Appendix D.

Remark 1 shows that the asset classification effect cannot be turned into arbitrage profits. The economic interpretation of this result is that short-selling stocks to accommodate static investors' demand for equity assets yields no risk-adjusted expected excess returns. Thus, the impact of static investors' equity exposure on the valuation of the stock market cannot be arbitraged away. In other words, unconstrained dynamic investors cannot regard the prospect of forcing stock market valuation back to its fundamentals as an arbitrage opportunity. Interestingly, this argument continues to work when dynamic investors are risk neutral. In that case, the price pressure from static investors becomes even stronger, as dynamic investors no longer demand a compensation for flow risk, p_f. The following remark shows that the price pressure exerted by static investors does not die out over time.

Remark 2. Transversality Condition. The equilibrium valuation of the stock market in Proposition 1 does not satisfy the transversality condition.

Proof.

$$\lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*[P_{t+h}] = \lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*[\text{PDV}(D_{t+h}) + p_f + \theta V_{t+h}] = p_f + \theta V_t. \tag{14}$$

The first equality follows from Proposition 1, and the second from Equations (10) and (13). Q.E.D.

Remark 2 shows that the asset classification effect survives discounting. Investors do not rationally expect the stock market valuation to eventually converge to its fundamental value. This is due to the infinite maturity of equity assets and the perpetual nature of the expected demand pressure.[9] Dynamic investors are not subject to any portfolio constraint. Yet, maintaining a short position indefinitely without ever realizing any gains is not optimal. Static investors' equity exposure is thus fully consistent with the workings of arbitrage by dynamic investors.

Remarks 1 and 2 demonstrate that the asset classification effect shares similarities with a rational bubble. Importantly, however, it is not a sunspot equilibrium driven by self-fulfilling beliefs. In Proposition 1, the asset classification effect is solely determined by static investors' allocation of capital to equity assets, which has a clear interpretation as an objective feature of the economy. This mechanism sets it apart from an extraneous sunspot that has nothing to do with the economy, as those criticized by Woodford (1987). Indeed, the rational price deviation from fundamentals discussed in this paper is pinned down by static investors' assets under management and target equity exposure. Thus, it can be *measured* using portfolio holdings data. Accordingly, the price deviation from fundamentals under consideration unwinds only if investors adopting static asset allocation strategies (such as balanced mutual funds and ETFs) drop their equity allocation targets or are forced into liquidation by wealth outflows.

Corollary 1. Stock Market Valuation, Fundamentals, and the Asset Classification Effect.

$$P_t = \underbrace{\mathbb{E}_t^*\left[\int_t^\infty e^{-r(s-t)} D_s \, ds\right]}_{Fundamentals} + \underbrace{\lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*\left[\theta V_{t+h}\right]}_{Asset\ Classification\ Effect} \tag{15}$$

Proof. The statement follows from Proposition 1 and Remarks 1 and 2.

Corollary 1 is an equivalent representation of Proposition 1. This result offers an alternative interpretation of the *Asset Classification Effect* as the rational expectation of the future level of wealth invested in that asset class under static asset allocation strategies. Naturally, because these expectations are taken under the risk-adjusted measure, they incorporate a compensation for flow risk.

Before proceeding with the analysis, I examine whether the asset classification effect is an artifact of restrictive assumptions. For example, asset allocation targets often allow for limited flexibility (Buffa et al., 2022). However, flexible asset allocation targets tend to only partially

[9]The micro-foundation in Appendix A emphasizes static investors as perpetual institutions whose shareholder base turns over continuously. Each individual retail investor plans to consume the present value of her wealth. However, the continual arrival of new generations of retail investors perpetuates the fund's wealth under management. This mechanism is reminiscent of that generating rational bubbles in overlapping-generations economies (Tirole, 1985; Weil, 1989). Arguably, it is based on realistic assumptions, because retail investors do form overlapping generations, and institutional investors operating under static asset-allocation strategies survive, in aggregate, beyond each individual cohort.

adjust to news. The residual degree of rigidity in asset allocation targets preserves the validity of the results, as discussed in Internet Appendix A. Moreover, investments under static allocation strategies may partly reflect information about fundamentals. For example, during a crisis, static investors are more likely to experience outflows. However, to the extent that some of the retail fund shareholders are inertial (see, e.g., Calvet et al., 2009), wealth flows and earnings news are only partly correlated. As discussed in Internet Appendix B, correlation between earnings news and wealth flows preserves the results. Additionally, static investors may adjust their holdings of individual stocks to engage in market timing. The analysis of the cross-section of stocks in Section 3 confirms that the results are robust to this consideration. Introducing a stochastic risk-free rate as in Merton (1973) would generate an additional hedging motive for dynamic investors. As static investors would not adjust to changes in the investment opportunity set, this extension would make the economic intuition for the asset classification effect even starker. Finally, the CARA utility of dynamic investors is tractable but prevents wealth effects. Appendix F relaxes this assumption by allowing dynamic investors to have general preferences. The asset classification effect remains robust to all of these considerations, suggesting that the economic force underlying it can be attributed to the static asset allocation strategy rather than to specific modeling choices.

Moreover, one may wonder whether the equilibrium pricing function is uniquely determined. As is usual in the stochastic control literature, Proposition 1 is obtained by ansatz and verification, which establishes the validity of the solution but does not rule out alternative solutions. I next show that a price deviation from fundamentals is a necessary feature of the equilibrium.

Remark 3. Necessity of a Deviation from Fundamentals. If $\lim_{h\to\infty} \mathbb{E}_t^*\left[e^{-rh}X_{t+h}P_{t+h}\right] = 0$, static investors induce a deviation between the equity asset class valuation and its fundamentals,

$$P_t = \mathbb{E}_t^*\left[\int_t^\infty e^{-r(s-t)}D_s\, ds\right] + \lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*\Big[\theta V_{t+h}\Big]. \tag{16}$$

Proof. By iterating forward the dynamic no-arbitrage restriction, $P_t = e^{-rdt}\mathbb{E}_t^*[P_{t+dt} + D_t dt]$,

$$\begin{aligned} P_t &= \mathbb{E}_t^*\left[\int_t^{t+h} e^{-r(s-t)}D_s ds + e^{-rh}P_{t+h}\right] \\ &= \mathbb{E}_t^*\left[\int_t^{t+h} e^{-r(s-t)}D_s ds\right] + \mathbb{E}_t^*\left[e^{-rh}X_{t+h}P_{t+h}\right] + \theta\mathbb{E}_t^*\left[e^{-rh}V_{t+h}\right], \end{aligned} \tag{17}$$

since Equations (4) and (6) imply that $P_t = (X_t + Q_t)P_t = X_tP_t + \theta V_t$. Equation (16) then follows by taking the limit for $h \to \infty$ in Equation (17), and applying the condition $\lim_{h\to\infty} \mathbb{E}_t^*\left[e^{-rh}X_{t+h}P_{t+h}\right] = 0$. Remark 1 implies that $\lim_{h\to\infty} e^{-rh}\mathbb{E}_t^*[\theta V_{t+h}] = p_f + \theta V_t$, which is, in general, different from zero. Q.E.D.

A related question is whether static investors survive in the long run. The portfolio choice of dynamic investors is relatively more efficient than that of static investors, and their wealth share can therefore be expected to rise over time. However, agents' survival and their price impact are two independent concepts (Kogan et al., 2006). Dynamic investors may accumulate wealth faster over time, but their asset demand is state contingent and thus cannot be anticipated. Static investors, by contrast, commit to a pre-specified asset allocation. Hence, given their current wealth, their future demand for equities is predictable. It is this predictability that allows static investors' asset demand to be reflected in current stock prices. Thus, the asset classification effect depends on the level of static investors' wealth, not on their share of aggregate wealth. An interesting implication of the equilibrium with dynamic and static investors is that the price impact of a trade depends on the intertemporal investment approach of its initiator. Stock purchases by dynamic investors are state contingent and do not generate any price pressure, as they merely impound news into the equilibrium price. Only stock purchases initiated by static investors generate price pressure that cannot be justified by news. This is because static investors purchase stocks due to their commitment to maintaining a static asset allocation, and regardless of news. This observation offers a new perspective on the literature estimating the aggregate stock market elasticity, namely, the price increase resulting from each dollar of equity purchases (Gabaix and Koijen, 2023). It suggests that before assessing how the stock market responds to an investment, one should consider the *strategy* behind that investment.

Turning to the equilibrium portfolio holdings, Equation (B.32) in Appendix B shows that

$$X_t^\star = \frac{\mu_t - rP_t + D_t}{r\gamma\sigma_t^2} - (1-\theta)\frac{Q_t p_D^2\omega^2 + \theta\pi^2}{p_D^2\omega^2 + \theta^2\pi^2}. \tag{18}$$

Equation (18) shows that dynamic investors' stock holdings, $X_t^\star$, increase with expected stock returns per unit of variance and decrease with the risk-free rate. Beyond this instantaneous risk-return tradeoff, their optimal portfolio also contains an intertemporal hedging component, whose magnitude increases in static investors' ownership share of the stock market, Q_t. When static investors become larger owners of the stock market, prices become relatively more driven by their wealth than by dividends. This makes the stock market less attractive as a vehicle to finance future consumption, because high static ownership tends to coincide with lower future expected returns and greater exposure to non-fundamental price volatility. Thus, as the stock market ownership share of static investors rises, dynamic investors tilt their portfolios away from equity assets.

The market clearing condition in Equation (6), together with Proposition 1 and static investors' stock market ownership share, $Q_t = \theta V_t/P_t$, implies that the equilibrium holdings of

dynamic investors can be characterized as follows.

$$X_t^\star = \frac{\text{PDV}(D_t) + p_f}{P_t}. \tag{19}$$

Equation (19) shows that, as the present discounted value of the dividend stream accounts for a larger proportion of the stock market valuation, the fraction of equity assets held by dynamic investors rises. Thus, all else equal, as the present discounted value of the dividend stream rises, dynamic investors take comparatively more aggressive positions in stocks. This statement could be looked at another way. For stock prices to accurately reflect future dividends, it is essential that dynamic investors find it optimal to allocate resources to the stock market.[10] Instead, when dynamic investors reduce their equity exposure, the present value of the dividend stream becomes a relatively less important determinant of of stock market valuation. Thus, in bad times, the wealth of static investors accounts for a relatively larger fraction of the price of equity assets.

Corollary 2. Expected Returns and Static Investors' Ownership. The expected return on the stock market is decreasing in the ownership share of static investors, Q_t.

Proof. See Appendix G.

Corollary 2 relates static investors' ownership share to stock market expected returns. To sharpen this result, the following remark shows that the ownership share of static investors shapes one of the most prominent predictors of expected stock returns, the dividend yield.

Remark 4. Dividend Yield Decomposition. The dividend yield admits the decomposition

$$y_t = \tilde{y}_t - z_t, \tag{20}$$

where

$$y_t = \log(D_t/P_t), \qquad \tilde{y}_t = \log[D_t/(P_t - \theta V_t)], \qquad z_t = -\log(1 - Q_t). \tag{21}$$

Proof. The statement is an identity that follows from the definition $Q_t = \theta V_t/P_t$. Q.E.D.

The equilibrium valuation of the stock market reflects both the risk-adjusted present value of the dividend stream and the equity exposure of static investors. The dividend yield conflates these two forces. A low dividend yield could mean that the market anticipates strong dividends, or it could mean that a large amount of wealth is allocated to the stock market by static investors, who exert aggregate price pressure. The dividend yield, y_t, cannot tell these two stories apart.

[10] Indeed, under the earnings process of Equation (1), $\text{PDV}(D_t)$ is the best linear unbiased estimator of the dividend stream. Equation (19) shows that $P_t = \text{PDV}(D_t) + p_f$ when $X_t = 1$, at which point the stock market valuation most accurately forecasts the dividend stream.

Remark 4 thus decomposes the dividend yield into two terms: $\tilde{y}_t$, the ratio of dividends to the component of stock market valuation reflecting future dividends, and z_t, an increasing function of static investors' ownership share of the stock market. If Corollary 2 is correct, the component of the dividend yield associated with static investors' stock market ownership share should negatively predict future returns, offering a natural empirical testing ground for the model.

Overall, this section has demonstrated the presence of the asset classification effect under fairly general conditions. According to this effect, the aggregate market value of equity assets increases with the equity exposure of investors adhering to static asset allocation strategies.

3 The Cross-Section of Stocks

The results presented thus far, which characterize the aggregate stock market in the time series, open the door to an important question: Which stocks exhibit the strongest price responses, when the wealth of static investors rises? To address this question, one has to examine not only investors' asset allocation, but also their stock selection. To parsimoniously extend the model in this direction, investors are distinguished based on their degrees of freedom in portfolio management. Dynamic investors are treated as unconstrained agents engaging in both optimal asset allocation and optimal stock selection.[11] Static investors are divided into two groups: *Stock pickers*, who select stocks optimally while adopting a static asset allocation strategy; *Index trackers*, who track a benchmark index and adopt a static asset allocation strategy.

3.1 Assets

The economy features I stocks. The real earnings, E_{it}, underlying stock i at time t follow

$$dE_{it} = m_i dt + \omega_i dB_{it}, \tag{22}$$

where m_i denotes the expected growth of earnings and ω_i their volatility, and B_{it} is a Brownian motion. The pairwise instantaneous correlation between earnings news is $dB_{it}dB_{jt} = \varrho_{ij}dt$. Firm i pays aggregate real dividends at rate $D_{it} = aE_{it}$ with a constant payout ratio $a = 1$. Stock shares trade at the real price P_{it}, with price drift and diffusion coefficients μ_{it} and σ_{it}, respectively. The covariance between the price changes of stocks i and j is denoted by σ_{ijt}. To ensure that the individual earnings aggregate to the total earnings in the economy in Equation (1), impose the restrictions $m = \sum_{i=1}^{I} m_i$ and $\omega = \sqrt{\sum_i \sum_j \omega_i \omega_j \varrho_{ij}}$.

Each firm's fixed outstanding equity is represented by one normalized share, $S_i = 1$, whose price equals the firm's market capitalization. The aggregate valuation of the equity asset class

[11] For simplicity of exposition, I abstract from cross-sectional portfolio constraints on dynamic investors, treating all of them as unconstrained.

from Section 2 is thus

$$P_t = \sum_{i=1}^{I} P_{it}. \tag{23}$$

There is one stock market index consisting of a collection of $N \leq I$ stocks. The index level is

$$P_t^{\text{IDX}} = \sum_{i=1}^{I} N_i P_{it}. \tag{24}$$

The indicator variable N_i equals 1 if stock i is included in the index and 0 otherwise. Because the supply of shares is held constant across stocks, float-adjusted market capitalization index weights coincide with price weights. Each stock's index weight is therefore given by its price relative to the index level and denoted by $\lambda_{it} = N_i P_{it}/P_t^{\text{IDX}}$.

3.2 Dynamic Investors

The wealth of dynamic investors evolves as in Merton (1973). Namely,

$$dW_t = (rW_t - c_t)dt + \sum_{i=1}^{I} X_{it}[(D_{it} - rP_{it})dt + dP_{it}]. \tag{25}$$

Their derived utility function and related transversality condition were specified in Section 2.2. Dynamic investors optimally select the number of shares of each stock, X_{it}. The aggregate stock market ownership share of dynamic investors is $X_t = \sum_i X_{it}$.

3.3 Static Investors

Static investors allocate a proportion θ of their wealth to the stock market. There are two groups of static investors: *Stock Pickers* (active investors), and *Index Trackers* (passive investors). The wealth of static investors is the sum of the wealth of stock pickers and index trackers. Namely, $V_t = V_t^A + V_t^P$, where V_t^A and V_t^P denote the wealth of stock pickers and index trackers, respectively. The wealth flows to static investors, dF_t, are split between the two groups of static investors through constant loadings: stock pickers receive π^A, and index trackers $\pi^P = \pi - \pi^A$. The number of shares of the i-th stock held by static investors is denoted by $Q_{it} = Q_{it}^A + Q_{it}^P$, where Q_{it}^A and Q_{it}^P denote the number of shares held by stock pickers and index trackers, respectively.

3.3.1 Stock Pickers

Stock pickers adopting a static asset allocation strategy have target allocation θ to equity assets. Their wealth evolves as follows.

$$dV_t^A = rV_t^A(1-\theta)dt + \sum_{i=1}^{I} Q_{it}^A \left(dP_{it} + D_{it}dt\right) + \pi^A dF_t. \tag{26}$$

Equation (26) highlights that stock pickers do not regard the risk-free rate as the opportunity cost of their individual stock positions, as their allocation to equity assets is predetermined. Stock pickers select their cross-sectional stock holdings, Q_{it}^A, as a solution to the constrained mean-variance portfolio optimization problem:

$$\max_{\{Q_{it}^A\}} \left\{ \mathbb{E}_t \left[\sum_{i=1}^{I} Q_{it}^A (dP_{it} + D_{it}dt) \right] - \frac{\gamma}{2} \mathbb{E}_t \left[\left(\sum_{i=1}^{I} Q_{it}^A dP_{it} \right)^2 \right] \right\} \tag{27}$$

$$\text{s.t.} \qquad \sum_{i=1}^{I} P_{it} Q_{it}^A = \theta V_t^A. \tag{28}$$

In Equation (27), the parameter capturing the degree of risk aversion of stock pickers, γ, is the same risk-aversion parameter used for dynamic investors.[12] Hence, stock pickers adopting a static asset allocation strategy differ from dynamic investors because the proportion of their wealth invested in stocks, θV_t^A, is fixed rather than sensitive to news. The optimal number of shares of the i-th stock held by stock pickers is denoted by $Q_{it}^{A\star}$. The associated equity-sleeve weight is denoted by $q_{it}^\star$ and results from the accounting identity $Q_{it}^{A\star} = q_{it}^\star \theta V_t^A / P_{it}$.

3.3.2 Index Trackers

Index trackers adopting a static asset allocation strategy have target allocation θ to equity assets. The number of shares of the i-th stock held by index trackers is proportional to the index weight of that stock, λ_{it}, and thus equal to $Q_{it}^P = \lambda_{it}\theta V_t^P / P_{it}$. Their wealth evolves as follows.

$$dV_t^P = rV_t^P(1-\theta)dt + \sum_{i=1}^{I} Q_{it}^P \left(dP_{it} + D_{it}dt\right) + \pi^P dF_t. \tag{29}$$

[12] This choice is a parsimonious normalization that aims to level the playing field between the preferences toward risk of dynamic investors and static stock pickers, so that differences in the portfolio choices of these agents can be attributed to their asset allocation strategies.

3.4 Market Clearing

The financial market clears for each of the I stocks. For the i-th stock,

$$\underset{\downarrow}{\text{Dynamic Investors}} \qquad \underset{\downarrow}{\text{Stock Pickers}} \qquad \underset{\downarrow}{\text{Index Trackers}}$$
$$X_{it} \quad + \quad Q_{it}^{A} \quad + \quad Q_{it}^{P} \quad = \quad S_i. \tag{30}$$

The next proposition characterizes the cross-section of equilibrium stock prices by combining agents' asset demands with the market clearing condition for each individual stock.

Proposition 2. The Cross-Section of Equilibrium Stock Prices.

$$P_{it} = \underbrace{\mathbb{E}_t^* \left[\int_t^\infty e^{-r(s-t)} D_{is}\, ds \right]}_{Fundamentals} + \underbrace{p_{f_{it}}^A + q_{it}^\star \theta V_t^A + \overbrace{p_{f_{it}}^P + \lambda_{it} \theta V_t^P}^{Index\ Inclusion}}_{Asset\ Classification}$$

where $p_{f_{it}}^A = -\gamma \pi \theta \pi^A q_{it}^\star$ and $p_{f_{it}}^P = -\gamma \pi \theta \pi^P \lambda_{it}$ are the risk adjustments induced by stochastic wealth flows to active stock pickers and passive index trackers, respectively.

Proof. See Appendix H. The appendix also reports the optimal portfolio and consumption choices maximizing dynamic investors' HJB and solves stock pickers' mean-variance problem.

Proposition 2 is the second central result of this paper. It shows that the price of each stock reflects its *Fundamentals*, the expected cash flows and the discount rates required by dynamic investors—which adjust for the correlations with other stocks and flow risk, as discussed later. Above and beyond its fundamentals, the price of each stock reflects its *Asset Classification*, and the resulting price pressure from static investors—both stock pickers and index trackers. The importance of this effect for the price of each stock corresponds to the wealth of static investors weighted by the share of that stock in their portfolio. Static investors hold two categories of stocks: (i) index stocks, receiving investments from index trackers; and (ii) stocks with favorable risk-return profiles, attracting investments from stock pickers.

A large literature documents that stocks included in an index tend to trade at high valuations relative to their fundamentals due to the price pressure from index trackers, following the seminal evidence in Harris and Gurel (1986) and Shleifer (1986). In this model, the *Index Inclusion Effect* is due to the tracking constraint, which prevents index trackers from stock selection in the cross-section. Index trackers thus adhere to a policy of passively investing in each stock in proportion to its index weight, λ_{it}, leading index stocks to trade at high valuations relative to non-index stocks with an equivalent dividend stream. Importantly, Proposition 2 identifies another constraint on portfolio choice that impacts the price of individual stocks. Namely, the *Asset Classification* of a security generates price pressure, due to the static asset allocation con-

straint, θ, which prevents static investors from adjusting their exposure to equity assets over time. By adhering to a static asset allocation strategy, static investors lead individual stocks to trade at high valuations relative to their dividend stream (from the perspective of the unconstrained dynamic investors). The price pressure from asset classification encompasses all price pressure from static asset allocation strategies, of which the index inclusion is a special case that selectively applies to index stocks.

As Appendix H further shows, the i-th stock price admits the following representation:[13]

$$P_{it} = \text{PDV}(D_{it}) + p_{f_{it}} + \theta\big[q^{\star}_{it} V^A_t + \lambda_{it} V^P_t\big], \tag{31}$$

where $\text{PDV}(D_{it}) = p_{\gamma_i} + p_D D_{it} + p_m m_i$ denotes the present discounted value of the dividend stream of the i-th stock net of the risk adjustment $p_{\gamma_i} = -\frac{\gamma}{r^2}\sum_j \omega_i \omega_j \varrho_{ij}$. Each stock has a heterogeneous exposure to the risk of aggregate fund flows (Dou et al., 2025), which increases with its weight in the portfolio of static investors. The corresponding risk-adjustment term is $p_{f_{it}} = -\gamma\pi\theta(\pi^A q^{\star}_{it} + \pi^P \lambda_{it})$. Together, p_{γ_i} and $p_{f_{it}}$ adjust the price of a stock for the variance of its dividends, its correlation with other stocks' dividends, and its exposure to aggregate flows. Thus, the i-th stock's price exceeds the risk-adjusted present value of its dividends. However, there are no arbitrage opportunities, because the portfolio choices of dynamic investors and stock pickers ensure that each stock's risk-return profile is equalized in the cross-section.

Individual stocks contribute to the aggregate asset classification effect in proportion to their weight in the portfolio of static investors. This can be seen from the aggregation condition in Equation (23). Indeed,

$$\sum_i \Big[\text{PDV}(D_{it}) + p_{f_{it}} + \theta\big[q^{\star}_{it} V^A_t + \lambda_{it} V^P_t\big]\Big] = \text{PDV}(D_t) + p_f + \theta V_t. \tag{32}$$

Contrary to conventional wisdom, both groups of static investors exert pressure on stock prices. *Index trackers* are perhaps understood to do so, as they hold the index constituents in fixed proportions, regardless of the returns offered by non-index stocks or by the risk-free asset. *Stock pickers* also exert price pressure, even with their active approach to portfolio management, because they operate under a static asset allocation strategy—this may be surprising. In fact, stock pickers may excel at identifying a relative mispricing in the cross-section of stocks, and can also time the stock market by forming long-short positions that adjust their portfolio's exposure to the stock market risk. However, their target asset allocation remains a binding constraint. Relative to unconstrained dynamic investors, the static asset allocation strategy

[13] The right-hand sides of Proposition 2 and Equation (31) depend on the equilibrium price through λ_{it} and $q^{\star}_{it}$, whose expressions are provided in Equations (H.3) and (H.14), respectively. These equations thus characterize the equilibrium as a fixed point representation. This representation is interpretable, as it makes clear that a stock's price exceeds its risk-adjusted dividend stream by the amount of wealth invested in that stock by index trackers and stock pickers.

compels stock pickers to hold too much equity in bad times, and thus to establish excessively large positions in their best stock ideas; the opposite holds true in good times. This is clear from investors' optimal portfolio choices, as discussed below. Appendix Equation (H.8) derives the number of shares maximizing stock pickers' constrained mean-variance problem. Specifically,

$$Q_{it}^{A\star} = \frac{\mu_{it} - \xi_t P_{it} + D_{it}}{\gamma \sigma_{it}^2} - \sum_{j \neq i} \frac{Q_{jt}^{A\star} \sigma_{ijt}}{\sigma_{it}^2}, \tag{33}$$

where ξ_t is the Lagrange multiplier on stock pickers' asset allocation constraint ensuring that

$$\sum_{i=1}^{I} Q_{it}^{A\star} P_{it} = \theta V_t^A. \tag{34}$$

The constraint in Equation (34) is binding, because stock pickers are static investors. Increasing Q_{it}^A by one share necessarily forces an offsetting reduction in other equity holdings to satisfy the asset allocation target. Stock pickers thus regard ξ_t as the shadow price of investing in a stock. Economically, this corresponds to the marginal change in their mean-variance objective from relaxing Equation (34) by one unit of wealth. To put this into perspective, Appendix Equation (H.36) derives the portfolio choice maximizing the HJB for dynamic investors, reported below.

$$X_{it}^{\star} = \frac{\mu_{it} - r P_{it} + D_{it}}{r \gamma \sigma_{it}^2} - \frac{\sum_{j \neq i} X_{jt}^{\star} \sigma_{ijt}}{\sigma_{it}^2} - \frac{(1-\theta)}{\sigma_{it}^2} \frac{\text{Cov}_t(dP_{it}, dV_t)}{dt}. \tag{35}$$

A comparison of Equations (33) and (35) shows that the portfolio choice of dynamic investors differs from that of stock pickers in two regards: (i) Dynamic investors compare the investment in each stock against the opportunity cost offered by the risk-free rate, r, reflecting their flexibility to invest in the risk-free asset. Stock pickers instead face a purely cross-sectional problem, and compare the investment in each stock against the shadow cost of their static asset allocation constraint ξ_t.[14] (ii) Dynamic investors exhibit a hedging demand proportional to the term $\text{Cov}_t(dP_{it}, dV_t)$, which captures the contribution of each stock to the aggregate tilt in the equity exposure of dynamic investors induced by static investors. These two aspects, beyond representing an inefficiency from an investment perspective, lead stock pickers to induce price pressure. More precisely, by adopting static asset allocation strategies, stock pickers exert price pressure precisely on stocks they optimally select, leading these stocks to be priced coherently with other equity assets, but overpriced relative to the present value of the dividend stream (evaluated from the viewpoint of dynamic investors).

This analysis of the cross-section was deliberately kept simple to yield analytical tractability.

[14] The Lagrange multiplier ξ_t generally differs from the risk-free rate r. When the target equity exposure forces stock pickers to hold more stocks than they optimally would, $\xi_t > r$. Conversely, when it forces them to hold fewer stocks than they optimally would, $\xi_t < r$. Equality $\xi_t = r$ obtains only when the target equity exposure happens to correspond to the unconstrained optimum.

As discussed in the literature, stock pickers often evaluate their performance relative to an index (Basak and Pavlova, 2013). They frequently engage in style investing (Boyer, 2011), generating price pressure on groups of stocks bearing those style labels. Stocks are included in several indexes that vary in benchmarking intensity (Pavlova and Sikorskaya, 2023). The strength of the index inclusion effect varies over time (Chang et al., 2015; Greenwood and Sammon, 2025). The rise of passive investment (see, e.g., Jiang et al., 2025) implies that wealth flows are increasingly directed to index trackers rather than stock pickers. The present framework abstracts from these considerations, although the key economic forces identified here are likely to hold more broadly. Instead, it focuses on the relationship between stock-level price pressure and aggregate price pressure at the equity asset-class level, a relationship that has remained largely unexplored in prior research.

Overall, this section has derived the cross-section of equilibrium stock prices. The aggregate price pressure exerted by static investors has a stronger impact on index constituents, which attract the investment of index trackers, and on stocks with high and stable expected returns, which attract the investment of stock pickers operating under static asset allocation strategies.

4 Empirical Relevance

This section assesses the empirical relevance of the model. Specifically, it examines whether the empirical counterpart of static investors' equity exposure is large, persistent, and related to stock valuations and returns in the directions predicted by the model. Section 4.1 studies the aggregate stock market in the time series. Section 4.2 turns to the cross-section of stocks.

4.1 The Time Series

As shown in Lemma 1, in a benchmark economy populated only by dynamic investors, stock market valuation equals the present value of the aggregate dividend stream from the viewpoint of dynamic investors.[15] Relative to this benchmark, as shown in Proposition 1, the presence of static investors impacts the valuation of the stock market. Thus, under the assumptions maintained by the model, the stock market valuation in Proposition 1 exceeds that in Lemma 1 by an increment proportional to the equity exposure of static investors, which can be measured in the data. Static investors are institutional investors operating under static asset allocation strategies. To gauge their importance in the data, I examine mutual funds and ETFs, whose asset allocation can be observed with relatively high precision, enabling me to ascertain whether each fund follows a static asset allocation strategy. Other institutional investors, such as pension funds, insurance companies, and sovereign wealth funds, may also follow static allocation

[15] The notion that dynamic investors can adjust their asset allocation in response to market conditions to generate profits is hard to dispute. There is considerable evidence that dynamic asset allocation strategies can generate large alphas by reducing risk when volatility is high (Moreira and Muir, 2017) and after the onset of recessions (Gómez-Cram, 2022). The literature on dynamic portfolio choice is extensive (see, e.g., Campbell and Viceira, 1999; Brandt and Santa-Clara, 2006).

strategies, but are harder to observe with comparable granularity. This measurement of the importance of static investors is thus likely to be conservative.

The data on mutual funds and ETFs are obtained from the CRSP Survivor-Bias-Free US Mutual Fund Summary Files.[16] As this study focuses on the stock market, funds with CRSP objective codes beginning with "O" (Other), "I" (Fixed Income), "MT" (Mixed Target), or "EF" (Equity Foreign) are excluded.[17] The sample is restricted to funds open to investment. To mitigate reporting errors, observations with Total Net Assets (TNA) below $5 million are excluded. Following standard practices, share-class data are aggregated into data on unique portfolios. Fund-level variables, such as the fraction of the portfolio allocated to common stocks, are computed as the TNA-weighted average of the underlying share classes. Quality screens are applied to mitigate reporting errors: observations are excluded if the sum of fixed income and equity allocations exceeds 110%, or if the total reported fraction of the portfolio allocated across asset classes falls outside the [75%, 125%] range. The sample covers the period from 2003:Q1, the first quarter with reliable data, to 2024:Q4, and comprises 322,420 fund-quarter observations. Wealth flows to each fund are computed by comparing the change in each fund's TNA with the change implied by returns and mergers; any residual is attributed to net flows. This procedure follows Lou (2012).

Funds are then classified based on the stability of their asset allocation strategies. To this end, the standard deviation of the allocation of each fund to common stocks (CRSP variable: per_com) is computed, based on an expanding window of observations that uses only the fund's allocation history available up to that quarter, avoiding look-ahead bias. A minimum of eight quarters is required, so that the classification starts in 2004:Q4. Mutual funds and ETFs are classified as "static" if the standard deviation of their asset allocation is less than or equal to 5%. At this threshold, equity weights exhibit very modest time-series variation, rather than being state-contingent, consistent with static asset allocation strategies. This criterion identifies 6,386 funds that are classified as static in at least one quarter, meaning their entire equity allocation history up to that quarter exhibits very limited variation. By contrast, 3,475 funds are never classified as static, as their equity allocation varies consistently over time. The evidence of both dynamic and static asset allocation strategies even among mutual funds and ETFs supports the distinction between static and dynamic investors emphasized by the model.

Based on this criterion, the sample is then restricted to funds classified as static, which constitute a (conservative) empirical counterpart of the static investors discussed in the model. For each quarter, fund-level net wealth flows, TNA, and equity exposure are aggregated across static funds, to obtain a description of the sector of static investors. The share of the U.S. stock

[16] CRSP Summary Files are not affected by the data quality problems documented by Schwarz and Potter (2016), which primarily pertain to CRSP Holdings Files prior to 2008.

[17] Target-date funds are excluded from the sample for consistency with the theoretical model, which does not explicitly consider deterministic glide paths in static asset allocation targets. Again, this exclusion induces a conservative measurement of the importance of static investors.

TABLE 1: **Summary statistics of funds with static equity allocation.** The table reports annual statistics for static funds from the CRSP Mutual Fund Database. Static funds are defined as mutual funds and ETFs with standard deviation of the fraction of the portfolio allocated to common stocks $\leq 5\%$. The standard deviation is computed using only the fund's allocation history available up to each date. Wealth flows are annual totals computed following Lou (2012). TNA is aggregate total net assets across all static funds, expressed in trillions of dollars and measured at year end. U.S. Equity Exposure is the aggregate dollar exposure of static funds to U.S. equities, computed as the sum across funds of each fund's TNA multiplied by equity allocation, and measured at year end. Percentage of U.S. Stock Market Held by Static Funds is the ratio of Static Funds' U.S. Equity Exposure to U.S. Stock Market Capitalization measured at year end. Data from CRSP Mutual Fund Summary Files for the period 2004–2024.

Model Counterpart	πdF_t	V_t	θV_t	P_t	Q_t
Year	Wealth Flows ($Bn)	TNA ($T)	U.S. Equity Exposure ($T)	U.S. Stock Market Cap ($T)	% U.S. Stock Market Held by Static Funds
2004	23.21	2.22	2.05	16.46	12.45
2005	23.72	2.41	2.21	17.38	12.72
2006	-10.32	2.72	2.53	19.62	12.89
2007	23.02	3.10	2.88	20.22	14.26
2008	-16.63	1.94	1.77	12.14	14.59
2009	-20.36	2.43	2.23	15.83	14.08
2010	-77.53	2.76	2.59	18.52	14.00
2011	-63.25	2.64	2.41	17.90	13.48
2012	-76.80	2.87	2.63	20.39	12.90
2013	73.33	3.70	3.41	26.33	12.96
2014	-15.73	3.98	3.70	29.01	12.74
2015	-104.74	4.00	3.73	27.69	13.46
2016	-38.34	4.27	3.98	30.18	13.18
2017	-56.98	4.33	4.09	35.76	11.43
2018	-68.67	4.60	4.35	32.57	13.36
2019	-186.49	5.62	5.34	41.16	12.97
2020	-254.52	6.37	6.06	49.84	12.16
2021	39.41	7.37	7.03	63.18	11.12
2022	11.06	6.17	5.87	49.72	11.80
2023	-135.93	6.96	6.66	60.70	10.97
2024	86.54	7.89	7.55	74.03	10.20
Mean	-40.29	4.21	3.96	32.32	12.75

market held by static investors is then computed as the ratio of static funds' aggregate U.S. equity exposure to total U.S. stock market capitalization from CRSP.

Table 1 reports summary statistics for the static funds aggregate sample.[18] Despite the attention they have received, wealth flows are two orders of magnitude smaller in absolute value than the wealth managed under static asset allocation strategies. An augmented Dickey–Fuller test applied to the quarterly series of wealth flows to static funds rejects the null of a unit root with a t-statistic of -5.39, pointing to a stationary time series. By contrast, the TNA of static funds exhibits an upward trend, consistent with the model's assumptions.

[18] An alternative classification based on the coefficient of variation of the equity allocation, reported in Appendix Table I, yields similar results.

Proposition 1 shows that the presence of static investors impacts the equilibrium valuation of the stock market through the asset classification effect, which operates via two channels: the flow risk-adjustment, p_f, and the equity exposure of static investors, θV_t. The volatility of annual wealth flows, which can be inferred from Table 1 to be \$0.08 trillion, places the model parameter π at about 0.08. For reasonable values of the risk aversion coefficient, γ, the flow-risk adjustment component of the asset classification effect, $p_f = -\gamma\theta\pi^2$, is thus negligible relative to the equity exposure of static funds. The equity exposure of static funds, which proxies for θV_t, is illustrated in Figure 1. This exposure rises from \$2.05 trillion in 2004 to \$7.55 trillion in 2024, while U.S. stock market capitalization grows from \$16.46 trillion to \$74.03 trillion. The equity exposure of static funds is thus trending alongside the stock market valuation.

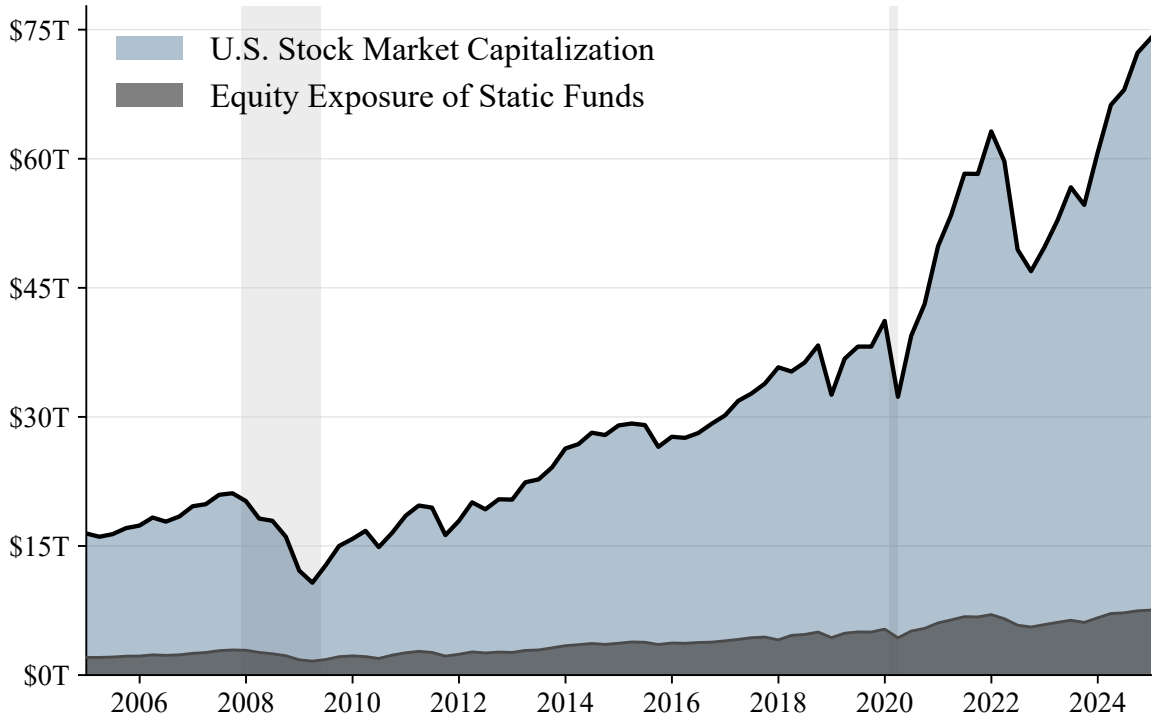


FIGURE 1: **U.S. stock market capitalization and exposure of funds with static equity allocation**. This figure plots the time series of aggregate U.S. stock market capitalization and the equity exposure of Mutual Funds and ETFs classified as following static asset allocation strategies. Funds are classified as implementing a static allocation to equity assets and labeled as "static funds" if their asset allocation to common equity has a standard deviation below 5%. The standard deviation is computed using only the fund's allocation history available up to each date. Gray shaded areas denote NBER recessions. Source: quarterly 2004–2024 CRSP data.

The asset classification effect discussed in Proposition 1 can be viewed through the lens of a price deviation from the risk-adjusted discounted value of the dividend stream. Detecting such a deviation in the data or rejecting its presence is no easy matter (Stiglitz, 1990).[19] Relative

[19]The pricing of claims on dividends at specific horizons could potentially offer a way forward. Unfortunately, claims on dividends are not

to much of the literature in this field, however, the model developed in this paper presents an advantage: the price deviation from economic fundamentals is pinned down by quantities that are observable in the data. According to the model, the asset classification effect is present, and data on static investors' TNA and target equity exposure can be used to gauge its magnitude.

I therefore examine whether static investors' equity exposure comoves with a recent estimate of a rational stock price bubble. Figure 2 compares the aggregate U.S. equity exposure of static funds, which proxies for θV_t, with the rational bubble measure of Andreasen and Bro (2026). Their present-value model uses stock market data and survey expectations to separate fundamentals from a rational bubble component, measured in log points of the S&P 500's price–dividend ratio. To obtain a dollar equivalent, I calculate the corresponding fraction of the index's value attributable to the bubble and multiply it by aggregate U.S. stock market capitalization from CRSP.[20] Comparing the two series shows that they display a strong comovement, with a correlation of 0.91. Static investors' equity exposure therefore tracks the evolution of the estimated rational bubble over time. This comovement provides suggestive support for the model's interpretation of θV_t as a bubble component of stock market valuation.

The asset classification effect is consistent with the literature on aggregate price pressure. This literature uses identification strategies based on variation in the level of wealth allocated to an asset class in settings plausibly unrelated to information about fundamentals. A strand of this literature presents evidence that unexpected mutual fund wealth flows are closely related to aggregate stock returns (Warther, 1995; Edelen and Warner, 2001; Ben-Rephael et al., 2011). In the model, this source of exogenous variation corresponds to a shift in fund flows, dF_t. Da et al. (2018) take a different approach. They examine the reallocation of wealth between funds with different target equity allocation, such as retail investors reallocating wealth from a 40% to a 60% equity mandate, showing that such reallocations exert aggregate price pressure on the stock market. In the model, this source of exogenous variation corresponds to a shift in the equity target, θ, of the aggregate static investor sector. Hartzmark and Solomon (2025) show that buying pressure from prespecified dividend payments predicts higher market returns, particularly when mutual fund dividend reinvestment rises. In the model, this corresponds to the dividend received by static investors, $Q_t D_t$, which is reinvested into the equity asset class. Fang and Goldstein (2025) show that predictable rebalancing trades to maintain portfolio weights across asset classes transmit shocks between the stock and the bond market. In the model presented in this paper, bond market returns affect the wealth of static investors through their bond allocation, $(1-\theta)V_t$, thus impacting the stock market valuation. Harvey et al. (2025) show that predictable rebalancing trades following stock market returns induce market-wide

available at long maturities. Giglio et al. (2024) develop a model to estimate the price of such claims, but their approach rules out stock price deviations from their risk-adjusted discounted dividend streams by assumption, through the imposition of a transversality condition.

[20] The larger bubble estimated by Andreasen and Bro (2026) is consistent with static investors accounting for only part of its magnitude.

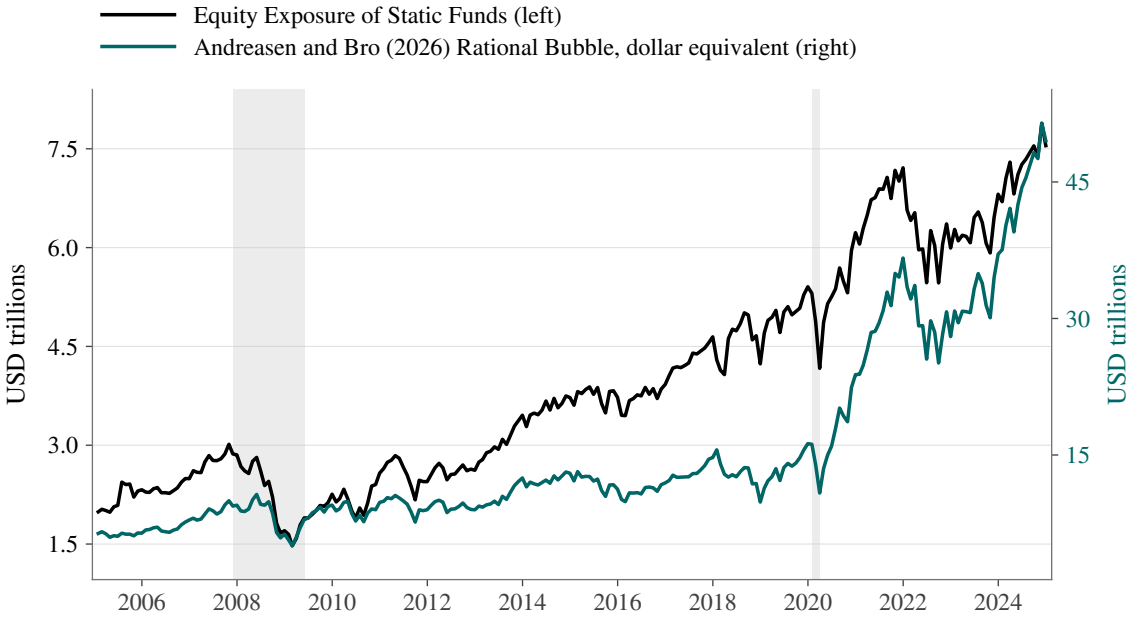


FIGURE 2: **Static investors' equity exposure and stock market rational bubble.** This figure plots the time series of aggregate U.S. equity exposure of Mutual Funds and ETFs classified as following static asset allocation strategies (left y-axis), and the rational bubble measure of Andreasen and Bro (2026) (right y-axis), expressed in dollar terms. Funds are classified as implementing a static allocation to equity assets and labeled as "static funds" if their asset allocation to common equity has a standard deviation below 5%. The standard deviation is computed using only the fund's allocation history available up to each date. Gray shaded areas denote NBER recessions. Source: quarterly 2004–2024 CRSP data and the replication files accompanying Andreasen and Bro (2026).

price impact. In the model presented in this paper, stock market returns affect the wealth of static investors through their equity allocation, θV_t, which induces portfolio rebalancing and associated price pressure. The model presented in this paper can explain (at least partly) each of these findings through a single mechanism. As illustrated in Equation (5), each of these channels captures a distinct source of variation in the equity exposure of static investors, thus generating aggregate price pressure on the stock market (Proposition 1).

Figure 3 shows the share of the U.S. stock market held by static funds, as a proxy for Q_t. Over the sample period, static funds held, on average, 12.75% of the U.S. stock market capitalization. This sizeable, but far from exhaustive, market share is consistent with financial markets featuring investors engaging in both dynamic and static asset allocation strategies, as assumed by the model. The figure also illustrates the realized Sharpe ratio on the U.S. stock market. The figure reveals a negative comovement between the two time series, which exhibit a correlation of -0.34 in levels and -0.61 in first differences. This stylized fact, while descriptive, suggests that funds maintaining a stable allocation to stocks tend to hold a larger fraction of the stock market when risk-adjusted stock realized returns deteriorate. The model rationalizes this pattern, because static investors keep a stable proportion of capital in stocks (Equation (4)),

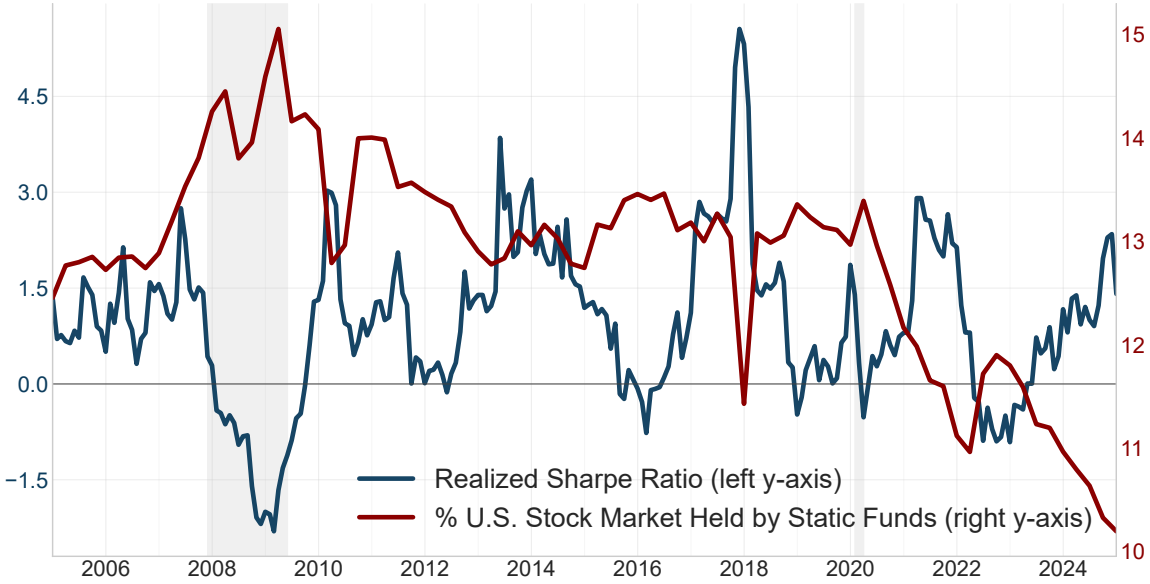


FIGURE 3: **U.S. stock market Sharpe ratio and ownership by funds with static equity allocation**. This figure displays the realized annual Sharpe ratio of the U.S. stock market (left y-axis) and the fraction of U.S. stock market capitalization held by Mutual Funds and ETFs with static allocation to equity assets (right y-axis). Funds are classified as implementing a static allocation to equity assets and labeled as "static funds" if their asset allocation to common equity has a standard deviation below 5%. The standard deviation is computed using only the fund's allocation history available up to each date. Gray shaded areas denote NBER recessions. Source: quarterly 2004–2024 CRSP data.

while dynamic investors time their exposure to stocks based on risk-adjusted expected returns (Equation (18)). In other words, static investors continue to hold stocks when it is inefficient to do so. Thus, the ownership share of static investors rises in bad times, consistent with the data.

To increase the size and resolution of the sample, I construct monthly data from the quarterly sample as follows. The CRSP Mutual Fund Database reports portfolio-level total net assets and equity allocations at a quarterly frequency in the Summary Files. Monthly TNA are available at the share-class level from the CRSP Monthly TNA Files. To ensure the two sources are aligned in the quarter in which both are observed, I compute a scaling factor equal to the ratio of TNA from the Summary Files to TNA from the Monthly Files evaluated at the same quarter-end. Each fund's quarter-end scaling factor is then applied uniformly to all months of the following quarter, avoiding any look-ahead bias in the construction of the monthly series. Each fund's equity target is also imputed to all months of the following quarter, consistent with the static asset allocation strategy that defines these funds. The data are then aggregated across funds, yielding a monthly version of the quarterly dataset that coincides with it at quarter ends.

The model delivers a testable prediction regarding the composition of the dividend yield. Remark 4 shows that the dividend yield admits the decomposition $y_t = \tilde{y}_t - z_t$. A high $\tilde{y}_t$ signals that stocks are cheap relative to their dividends, predicting higher future returns. A high z_t signals that stocks are expensive relative to their dividends, predicting lower future

TABLE 2: **U.S. stock market expected returns and ownership by funds with static equity allocation**. Panel A reports ordinary least squares monthly estimates of the regression

$$r^e_{t,t+h} = \alpha_h + \beta_h \tilde{y}_t + \gamma_h z_t + \varepsilon_{t+h}.$$

Panel B reports ordinary least squares monthly estimates of the benchmark regression

$$r^e_{t,t+h} = \alpha_h + \beta_h y_t + \varepsilon_{t+h}.$$

Panel C reports out-of-sample R^2 computed following Welch and Goyal (2008), using a recursive expanding window of 60 in-sample months. $r^e_{t,t+h}$ denotes the cumulative log market return in excess of the risk-free rate from month t to $t+h$. $y_t = \log(\frac{D_t}{P_t})$ denotes the dividend yield. In the model, the dividend yield admits the decomposition $y_t = \tilde{y}_t - z_t$, where $\tilde{y}_t = \log(\frac{D_t}{P_t - \theta V_t})$ and $z_t = -\log(1 - Q_t)$. t-statistics are computed using Hodrick (1992) standard errors and reported in brackets underneath the coefficients. One-sided p-values are used for $y_t > 0$, $\tilde{y}_t > 0$, and $z_t < 0$, as implied by the literature and the model. One, two, and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively. Monthly data from the CRSP Mutual Fund Summary Files for the period 2004–2024.

	2m	4m	6m	8m	10m	12m	14m	16m	18m
Panel A. Decomposed Specification									
$\tilde{y}_t$	0.090*	0.208**	0.378***	0.508***	0.642***	0.748***	0.843***	0.904***	1.004***
	[1.62]	[2.04]	[2.66]	[2.94]	[3.19]	[3.28]	[3.31]	[3.21]	[3.24]
z_t	−1.065*	−2.740**	−5.165**	−6.919**	−8.458**	−9.582**	−10.238**	−10.223**	−10.960*
	[−1.48]	[−1.89]	[−2.26]	[−2.26]	[−2.19]	[−2.04]	[−1.90]	[−1.67]	[−1.60]
$\overline{R}^2$	0.020	0.069	0.150	0.207	0.260	0.298	0.327	0.340	0.378
N	238	236	234	232	230	228	226	224	222
Panel B. Benchmark Specification									
y_t	0.046	0.098	0.176*	0.246*	0.330**	0.405**	0.486**	0.555**	0.640**
	[1.02]	[1.13]	[1.42]	[1.55]	[1.72]	[1.81]	[1.89]	[1.94]	[2.03]
$\overline{R}^2$	0.010	0.027	0.055	0.082	0.117	0.148	0.184	0.219	0.260
N	238	236	234	232	230	228	226	224	222
Panel C. Out-of-Sample R^2									
Decomposed	0.029	0.106	0.156	0.125	0.110	0.143	0.209	0.263	0.361
Benchmark	0.015	0.035	0.046	0.069	0.106	0.141	0.174	0.200	0.228
Difference	0.014	0.071	0.110	0.057	0.004	0.003	0.035	0.063	0.133
N	178	176	174	172	170	168	166	164	162

returns (Corollary 2). To examine this decomposition in the data, Table 2 estimates predictive regressions of cumulative log excess returns $r^e_{t,t+h}$. Panel A of the table reports ordinary least squares estimates of the regression

$$r^e_{t,t+h} = \alpha_h + \beta_h \tilde{y}_t + \gamma_h z_t + \varepsilon_{t+h}. \tag{36}$$

Panel B of the table reports ordinary least squares estimates of the benchmark regression

$$r^e_{t,t+h} = \alpha_h + \beta_h y_t + \varepsilon_{t+h}. \tag{37}$$

Equation (36) is the specification implied by the model, while Equation (37), which imposes the restriction that $\tilde{y}_t$ and z_t enter with equal and opposite coefficients, is a standard predictive regression. Both specifications are estimated at short and medium horizons $h \in \{2, 4, \ldots, 18\}$ months to keep the forecast horizon moderate relative to the sample length. The t-statistics, reported underneath the coefficient estimates, are based on Hodrick (1992) standard errors, which correct for the serial return correlation in predictive regressions. One-sided p-values are used, reflecting the sign restrictions $\beta_h > 0$ consistent with the literature (e.g. Fama and French, 1988) and $\gamma_h < 0$ implied by the model. Panel C reports out-of-sample R^2 statistics following Welch and Goyal (2008), computed over a recursive expanding window initialized with 60 in-sample months. They measure the reduction in mean squared prediction error of each specification relative to the forecast based on the historical average return.

Table 2 provides support for the model-implied decomposed specification in Equation (36). In Panel A, both components of the dividend yield have incremental predictive power with the signs predicted by the model: $\tilde{y}_t$ enters positively and significantly, whereas z_t enters negatively and significantly. The magnitude associated with z_t is economically large.[21] At the twelve-month horizon, an increase in z_t of one percentage point predicts lower cumulative excess returns of 9.582 percentage points. Panel B shows that the standard dividend yield achieves a substantially lower fit. At the six-month horizon, the in-sample $\overline{R}^2$ rises from 0.055 to 0.150 under the model-implied dividend-yield decomposition, and the out-of-sample R^2 improves by 0.11. Appendix Table II reports the same regressions estimated on the quarterly sample, confirming that the results are robust to the choice of sampling frequency.

These findings are consistent with the model, which shows that the dividend yield combines a component related to discounted dividends and a component related to ownership by static investors. This evidence supports the prediction that expected returns are associated not only with aggregate stock market valuation relative to dividends, but also with the extent to which that valuation reflects the wealth of static investors rather than the dividend stream.

4.2 The Cross-Section

Proposition 2 characterizes the cross-section of stock prices. It shows that, holding constant their expected dividend stream, stocks that are held more heavily by static investors command higher valuations. It follows that stocks more heavily held by static investors should trade at lower dividend yields. Testing this prediction requires a panel of stock-level ownership by institutional investors following static asset allocation strategies. The CRSP Summary Files allow one to classify funds as static and to measure their equity exposure, but do not report individual stock positions. I thus use the CRSP Mutual Fund Holdings Files to retrieve quarterly

[21] Regressors depending on market prices may bias predictive regressions (Stambaugh, 1999). Here, a positive return lowers z_t, positively biasing $\hat{\gamma}_h$. As the model predicts $\gamma_h < 0$, this upward bias attenuates the estimates toward zero, making the documented effect conservative.

data on the individual stock positions of the funds classified as static in Section 4.1.

The sample based on the CRSP Holdings Files begins in 2008:Q1, as earlier data from this source are subject to documented quality concerns (Schwarz and Potter, 2016). As the CRSP Mutual Fund Holdings Files are subject to data-quality limitations, I also obtain LSEG Mutual Fund Holdings data as an alternative sample for robustness purposes. The sample based on the LSEG Holdings Files begins in 2004:Q3, after the introduction of mandatory quarterly portfolio disclosure for mutual funds through Form N-Q. I use each of these two samples separately to compute, for each stock i and quarter t, the fraction of shares outstanding held by static funds, which serves as a proxy for Q_{it}.

Equity market data are drawn from CRSP for all ordinary domestic common shares listed on NYSE, AMEX, and NASDAQ. To mitigate the influence of micro-cap stocks, I exclude observations with a share price below five dollars and observations falling in the bottom market capitalization decile in each quarter. Dividend yields are constructed from CRSP monthly return data as the difference between total and ex-dividend returns, cumulated over the trailing twelve months. As the dependent variable is the log dividend yield, non-dividend-paying stocks are excluded from the sample. Firm-level book equity, leverage, and asset growth are obtained from Compustat. Observations with negative book equity are removed. This stock-level sample is then merged separately with CRSP Holdings File ownership data and LSEG Holdings File ownership data, yielding two independent panels. I then estimate panel regressions of the form

$$\log(D_{it}/P_{it}) = \beta_q \, Q_{it} + \Gamma' \, \Xi_{it} + \text{Fixed Effects} + \varepsilon_{it}, \tag{38}$$

where $\log(D_{it}/P_{it})$ is the log dividend yield of stock i at quarter t, Q_{it} is the fraction of its shares outstanding held by static funds, and Ξ_{it} is a vector of time-varying firm characteristics, including market capitalization, book-to-market ratio, leverage, and asset growth. The model predicts that the fraction of its shares outstanding held by static funds is associated with a lower dividend yield ($\beta_q < 0$).

Table 3 reports panel ordinary least squares estimates of Equation (38). Panel A presents estimates based on CRSP Holdings data. In column 1, the estimate of β_q is -1.765, with a t-statistic of -12.11, consistent with the model's prediction that higher ownership by static investors is associated with lower dividend yields. A natural concern is that static funds may systematically select stocks with low dividend yields, so that the coefficient estimate may reflect portfolio choice rather than price pressure. Columns 2 through 4 mitigate this concern by progressively introducing firm-level controls that capture common characteristics used by investors in stock selection. The coefficients on the control variables enter the regressions with the expected signs. The estimate of β_q remains negative and highly significant across specifications. Column 5 complements the analysis by including stock fixed effects, which absorb

TABLE 3: **U.S. stock dividend yields and ownership by funds with static equity allocation**. The table reports panel ordinary least squares estimates of quarterly regressions of stock-level dividend yields on the fraction of stock shares outstanding held by static funds,

$$\log(D_{it}/P_{it}) = \beta_q\, Q_{it} + \Gamma'\, \Xi_{it} + \text{Fixed Effects} + \varepsilon_{it}.$$

Two-sided t-statistics are reported in brackets underneath the coefficients. Standard errors are double-clustered at the firm and quarter level. One, two, and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively. R^2 denotes the squared correlation between the dependent variable and the linear predictor excluding fixed effects. Panel A is based on quarterly data from the CRSP Mutual Fund Holdings Files for the period 2008:Q1–2024:Q4. Panel B is based on quarterly data from the LSEG Mutual Fund Holdings Files for the period 2004:Q3–2024:Q4. The remaining variables are from CRSP and Compustat.

	1	2	3	4	5
Panel A. CRSP Holdings Files					
Q_{it}	-1.765^{***}	-1.757^{***}	-1.608^{***}	-1.696^{***}	-0.351^{**}
	$[-12.11]$	$[-12.04]$	$[-10.57]$	$[-11.05]$	$[-2.51]$
Market Cap$_{it}$		-0.412^{**}		-0.362^{*}	-0.747^{***}
		$[-2.13]$		$[-1.89]$	$[-4.26]$
BTM$_{it}$			0.129^{***}	0.135^{***}	0.280^{***}
			$[3.48]$	$[3.62]$	$[10.55]$
Leverage$_{it}$				0.319^{***}	-0.029
				$[3.91]$	$[-0.28]$
Asset Growth$_{it}$				-0.113^{***}	-0.076^{***}
				$[-3.97]$	$[-4.78]$
Time FE	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	No	No	Yes
R^2	0.043	0.044	0.051	0.058	0.031
N	89,927	89,927	89,927	89,869	89,869
Panel B. LSEG Holdings Files					
Q_{it}	-1.975^{***}	-1.966^{***}	-1.812^{***}	-1.908^{***}	-0.502^{***}
	$[-14.01]$	$[-13.93]$	$[-12.44]$	$[-12.91]$	$[-4.12]$
Market Cap$_{it}$		-0.346^{*}		-0.293	-0.715^{***}
		$[-1.70]$		$[-1.45]$	$[-4.33]$
BTM$_{it}$			0.145^{***}	0.152^{***}	0.240^{***}
			$[4.00]$	$[4.16]$	$[6.28]$
Leverage$_{it}$				0.378^{***}	0.180^{*}
				$[4.87]$	$[1.90]$
Asset Growth$_{it}$				-0.153^{***}	-0.091^{***}
				$[-5.27]$	$[-6.16]$
Time FE	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	No	No	Yes
R^2	0.037	0.037	0.048	0.058	0.044
N	111,101	111,101	111,101	111,028	111,028

time-invariant stock characteristics. Identification in this specification relies exclusively on within-stock variation in the fraction of shares held by static funds and in the dividend yield of each stock. The estimate of β_q remains negative and statistically significant at -0.351. The attenuation of the estimate relative to the other specifications is expected, given that stock fixed effects remove the permanent component of the association. At the same time, this estimate based on within-stock variation indicates that the result is not solely driven by time-invariant stock characteristics. Every specification includes time fixed effects, which absorb aggregate variation in dividend yields across quarters.

Panel B of Table 3 replicates the analysis using an alternative sample drawn from the LSEG Mutual Fund Holdings Files. The results are closely aligned with those in Panel A, with the estimate of β_q ranging from -1.975 in the baseline to -0.502 with stock fixed effects. The consistency across two alternative data sources mitigates data quality concerns specific to either. In the most saturated specifications, a one-percentage-point increase in the ownership by static investors is associated with 35 to 50 basis points lower log dividend yield, depending on the data source, pointing to an economically meaningful magnitude. Taken together, the findings in this table are consistent with the prediction of the model that static investors' equity exposure helps explain the cross-section of stock valuations.

5 Conclusion

This paper examines the importance of capital allocation strategies for the valuation of stocks. To this end, it develops an intertemporal capital asset pricing model with investors operating under dynamic and static asset allocation strategies. Solving the model in closed form shows that investors operating under static asset allocation strategies exert price pressure on the securities classified within the equity asset class. This tractable theory highlights continued demand pressure as a novel asset pricing mechanism through which price pressure on perpetual assets is compatible with the absence of arbitrage.

This finding offers a potential explanation for studies documenting evidence of aggregate price pressure exerted by wealth flows to the stock market. At the same time, it integrates wealth flows into a broader quantity that matters for asset prices: the level of wealth invested under static asset allocation strategies. Empirically, this variable is large, persistent, and associated with stock valuations and returns in the directions predicted by the model.

A broader implication of this paper is that the classification of a security into an asset class matters for its pricing whenever static asset allocation strategies specify target exposures to that asset class. This implication is relevant to policy proposals that encourage institutional investors to revise their allocation targets to stimulate domestic financial markets. The analysis in this paper is confined to the valuation of the equity asset class. The extent to which static asset allocation strategies shape the valuation of other asset classes is left for future research.

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Appendix

A Micro-foundation of the Economy

A.1 Environment

The economy is populated by a continuum of retail agents living in overlapping generations. Agents' lifetimes are exponentially distributed, as in the perpetual youth models of Yaari (1965) and Blanchard (1985). The j-th retail agent holds wealth W_{jt} and discounts the future at a constant rate δ, which incorporates both time preferences and mortality risk. Specifically, survival over horizon h occurs with probability $e^{-\tau h}$, where τ denotes the instantaneous hazard rate. At birth, each agent permanently adopts one of two investment strategies: *Dynamic* or *Static*. Agents have no bequest motive. Upon death, each agent exits the economy and is replaced by a newborn who inherits the predecessor's wealth and follows the same strategy. This environment facilitates aggregation.

A.2 Dynamic Investors

Retail agents adopting the dynamic investment strategy continuously observe financial markets and optimize their consumption and portfolio rules accordingly. They work professionally in financial markets rather than receiving labor income. Incorporating labor income would be feasible, but would not affect the mechanism emphasized here. The value function for an agent adopting the dynamic strategy, denoted by J^D, solves the following optimization program:

$$J^D(W_{jt}, V_t, t) \equiv \max_{\{c_{js}, X_{js}\}} \quad \mathbb{E}_t\left[\int_t^\infty e^{-\delta s} U(c_{js})\, ds\right], \tag{A.1}$$

$$\text{s.t. } dW_{jt} = (rW_{jt} - c_{jt})dt + X_{jt}dY_t, \qquad \lim_{h\to\infty} \mathbb{E}_t\Big[J^D(W_{jt+h}, V_{t+h}, t+h)\Big] = 0. \tag{A.2}$$

Let $\mathcal{D}_t$ denote the set of agents alive at time t who adopt the dynamic strategy. The aggregate wealth, consumption, and equity holdings of dynamic investors are continuous at the points of generational turnover. Collectively, dynamic investors have aggregate wealth $W_t = \int_{\mathcal{D}_t} W_{jt}dj$, aggregate consumption $c_t = \int_{\mathcal{D}_t} c_{jt}dj$, and aggregate equity holdings $X_t = \int_{\mathcal{D}_t} X_{jt}dj$. This aggregation requires that optimal policies are affine in or independent of individual wealth. In this case, the value function, dynamic budget constraint, and transversality condition presented in Section 2.2 produce solutions that characterize the aggregate consumption and investment paths of dynamic investors. Dynamic investors are best interpreted as the aggregate sector of financially sophisticated households and institutional investors engaging in dynamic asset allocation strategies, such as hedge funds and family offices.

A.3 Static Investors

Retail agents adopting the static strategy do not engage in continuous market observation. Rather, they work in the real economy and earn non-tradeable income, y_{jt}, with dynamics

$$dy_{jt} = \bar{y}_j dt + \tilde{\zeta} d\epsilon_{jt} + \pi dF_t, \tag{A.3}$$

where dF_t is an aggregate shock and $d\epsilon_{jt}$ is an idiosyncratic shock. Agents adopting the static strategy make consumption choices and invest their savings through the aggregate investment fund sector described in Section 2.3.[22] They are inertial households à la Brunnermeier and Nagel (2008), who adjust their fund exposure only infrequently. Portfolio inertia ensures that the stock market exposure of those retail investors does not systematically vary in response to market conditions. Moreover, they do not hedge against the state variable V_t. The value function for an agent adopting the static strategy, denoted by J^s, is determined by infrequently setting consumption and delegated investment, and solves the following optimization program:

$$J^S(W_{jt}, t) \equiv \max_{\{c_{js}\}\in\mathcal{A}_j^S} \quad \mathbb{E}_t\left[\int_t^\infty e^{-\delta s} U(c_{js})\, ds\right], \tag{A.4}$$

$$\text{s.t. } dW_{jt} = W_{jt}\left[(1-\theta)r dt + \theta\frac{dP_t + D_t dt}{P_t}\right] + dy_{jt} - c_{jt}dt, \ \lim_{h\to\infty} \mathbb{E}_t\Big[J^S(W_{jt+h}, t+h)\Big] = 0. \tag{A.5}$$

[22] Asset allocation targets can mitigate the agency costs of delegated portfolio management (He and Xiong, 2013).

Equation (A.4) illustrates the value function of the retail investors adopting the static strategy. $\mathcal{A}_j^S \equiv \{(c_{js})_{s\geq t} : c_{js} = c_{j,k},\ \text{for } s \in [t_{j,k}, t_{j,k+1})\}$ denotes the set of consumption plans that are only revised at investor-specific review dates. Between review dates, agents do not adjust their consumption and saving decisions in response to market conditions, capturing portfolio inertia. Equation (A.5) describes the wealth dynamics and the transversality condition for each agent adopting the static strategy. Specifically, their wealth grows by the return on their financial investments, which they achieve by acquiring exposure to funds adopting static asset allocation strategies, plus their labor income, dy_{jt}, minus their consumption, $c_{jt}dt$. Retail agents adopting the static strategy are best interpreted as inertial households who invest their savings through automatic investment plans into mutual funds and ETFs without continuously adjusting their exposure to market conditions.

Let $\mathcal{S}_t$ denote the set of agents alive at time t who adopt the static strategy. On aggregate, the investment fund sector manages $V_t = \int_{\mathcal{S}_t} W_{jt} dj$. As fund balances are inherited upon death, no wealth exits the fund due to mortality. Changes in V_t arise from investment returns on existing capital and from wealth flows. Namely,

$$dV_t = \underbrace{V_t\Big[(1-\theta)r dt + \theta(dP_t + D_t dt)/P_t\Big]}_{\text{capital revaluation}} + \underbrace{\int_{\mathcal{S}_t} (dy_{jt} - c_{jt}dt)dj}_{\text{fund flows}}. \tag{A.6}$$

The idiosyncratic income shocks and the timing of individual review dates average out across agents by the law of large numbers. Thus, the deterministic components of income deposits and consumption withdrawals aggregate into a constant drift term, under the maintained assumption that their cross-sectional distribution is stationary. That is,

$$\upsilon = \int_{\mathcal{S}_t} (\bar{y}_j - c_{jt})dj, \tag{A.7}$$

The aggregate component of the income shock, πdF_t, does not average out across agents. Equation (A.6) thus reduces to

$$dV_t = V_t\big[(1-\theta)r dt + \theta(dP_t + D_t dt)/P_t\big] + \upsilon dt + \pi dF_t. \tag{A.8}$$

Under the restriction $\upsilon = 0$, maintained for simplicity and subsequently relaxed in Appendix C, this expression corresponds to Equation (5). Retail investors lack bequest motives and plan to eventually consume their wealth, so that the following transversality condition holds:

$$\lim_{h\to\infty} \mathbb{E}_t[e^{-(r+\tau)h} W_{j,t+h}] = 0. \tag{A.9}$$

However, the investment fund sector operates as an institution whose horizon extends beyond

the lifetime of any individual shareholder. The wealth of the investment fund sector at any future date $t+h$ can be decomposed as

$$V_{t+h} = \underbrace{\int_{\mathcal{S}_t \cap \mathcal{S}_{t+h}} W_{j,t+h} dj}_{\text{survivors from date } t} + \underbrace{\int_{\mathcal{S}_{t+h} \setminus \mathcal{S}_t} W_{j,t+h} dj}_{\text{born after date } t}. \tag{A.10}$$

The first term in Equation (A.10) reflects the balances of agents alive at date t who survive to $t+h$. The fund balance of each of these agents satisfies the transversality condition in Equation (A.9). The second term in Equation (A.10) reflects the balances of agents born after date t, who finance part of their fund deposits from labor income earned after date t. The labor income of future generations does not enter the budget constraint of any agent alive at time t and is thus not constrained by their transversality conditions. As a result, the aggregate fund wealth V_{t+h} does not die out as h rises, although every agent alive today plans to consume their wealth, because the fund's wealth under management is continuously replenished by the labor income of newborn generations.

The equilibrium implications of this micro-foundation are discussed next. The arrival of new agents with non-traded sources of wealth creates the condition under which a rational asset price deviation from economic fundamentals can arise (Weil, 1989; Tirole, 1985). As newborns continually deposit non-tradeable labor income into the fund, the transversality conditions of the fund's current shareholders do not determine the long-run continuation value of the aggregate fund's equity exposure (characterized in Remark 2). It should be observed that the overlapping generations structure alone does not give rise to any price pressure. In fact, dynamic investors also feature generational turnover, yet no price pressure arises when only dynamic investors are present (Lemma 1). This would also be the case if dynamic investors were subject to labor income risk, which would simply generate a hedging term in their portfolio choice. Instead, price pressure arises because overlapping generations of inertial retail investors with non-tradeable income delegate their capital to institutional investors operating under static asset allocation strategies (Proposition 1).

B Proof of Proposition 1

As is standard in the literature, the proof proceeds by postulating that the pricing function is as guessed and verifying that the HJB equation and the market clearing condition are satisfied in equilibrium. The state variables follow the dynamics:

$$dD_t = mdt + \omega dB_t, \tag{B.1}$$

$$dV_t = rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi dF_t. \tag{B.2}$$

Substituting the dynamics of the state variables into the guess for the pricing function yields

$$P_t = p_\gamma + p_D D_t + p_m m + \theta V_t, \tag{B.3}$$

where $p_\gamma = -\gamma\big(p_D^2\omega^2 + \theta\pi^2\big)$, $p_D = \frac{1}{r}$, and $p_m = \frac{1}{r^2}$. The price dynamics are as follows.

$$dP_t = p_D dD_t + \theta\big[rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi dF_t\big]. \tag{B.4}$$

Equivalently,

$$dP_t = \frac{\frac{m}{r} + \theta[rV_t(1-\theta) + Q_t D_t]}{1-\theta Q_t}dt + \frac{p_D\omega}{1-\theta Q_t}dB_t + \frac{\theta\pi}{1-\theta Q_t}dF_t. \tag{B.5}$$

The price drift coefficient is given by

$$\mu_t = \frac{\frac{m}{r} + \theta[rV_t(1-\theta) + Q_t D_t]}{1-\theta Q_t}. \tag{B.6}$$

The price diffusion is the projection of the two independent Brownian increments, dB_t and dF_t, on the vector of their two respective loadings. Equivalently and more compactly, the price diffusion coefficient can be expressed as the corresponding scalar,

$$\sigma_t = \frac{\sqrt{p_D^2\omega^2 + \theta^2\pi^2}}{1-\theta Q_t}. \tag{B.7}$$

The HJB equation is

$$\begin{aligned} 0 &= \max_{\{c_t, X_t\}} \left\{ e^{-\delta t}U(c_t) + \frac{\mathbb{E}_t[dJ]}{dt} \right\} \\ &= \max_{\{c_t, X_t\}} \Bigg\{ e^{-\delta t}U(c_t) + J_t + J_W\mathbb{E}_t[dW_t] + J_V\mathbb{E}_t[dV_t] \\ &\qquad + \frac{1}{2}J_{WW}\mathbb{E}_t[dW_t^2] + \frac{1}{2}J_{VV}\mathbb{E}_t[dV_t^2] + J_{WV}\mathbb{E}_t[dW_t dV_t] \Bigg\}. \end{aligned} \tag{B.8}$$

The laws of motion of dynamic and static investors' wealth satisfy

$$dW_t = \big[rW_t - c_t + X_t(\mu_t - rP_t + D_t)\big]dt + \frac{X_t p_D\omega}{1-\theta Q_t}dB_t + \frac{X_t\theta\pi}{1-\theta Q_t}dF_t, \tag{B.9}$$

$$dV_t = \big[rV_t(1-\theta) + Q_t(\mu_t + D_t)\big]dt + \frac{Q_t p_D\omega}{1-\theta Q_t}dB_t + \frac{\pi}{1-\theta Q_t}dF_t. \tag{B.10}$$

The conditional first moments of dynamic and static investors' wealth changes are:

$$\mathbb{E}_t[dW_t] = [rW_t - c_t + X_t\big(\mu_t - rP_t + D_t\big)]dt, \tag{B.11}$$

$$\mathbb{E}_t[dV_t] = [rV_t(1-\theta) + Q_t(\mu_t + D_t)]dt. \tag{B.12}$$

The conditional second moments of dynamic and static investors' wealth changes are:

$$\mathbb{E}_t[dW_t^2] = \mathbb{E}_t[(X_t dP_t)^2] = (X_t\sigma_t)^2 dt, \tag{B.13}$$

$$\mathbb{E}_t[dV_t^2] = \frac{Q_t^2 p_D^2\omega^2 + \pi^2}{(1-\theta Q_t)^2}dt, \tag{B.14}$$

$$\mathbb{E}_t[dV_t dW_t] = \frac{X_t(Q_t p_D^2\omega^2 + \theta\pi^2)}{(1-\theta Q_t)^2}dt. \tag{B.15}$$

By substituting the above expressions into the HJB equation,

$$\begin{aligned}
0 = \max_{\{c_t, X_t\}} \Bigg\{ & e^{-\delta t}U(c_t) + J_t + J_W\mathbb{E}_t[dW_t] + J_V\mathbb{E}_t[dV_t] + \frac{1}{2}J_{WW}\mathbb{E}_t[dW_t^2] \\
& + \frac{1}{2}J_{VV}\mathbb{E}_t[dV_t^2] + J_{WV}\mathbb{E}_t[dW_t dV_t]\Bigg\} \\
= \max_{\{c_t, X_t\}} \Bigg\{ & e^{-\delta t}U(c_t) + J_t + J_W\big[rW_t - c_t + X_t(\mu_t - rP_t + D_t)\big] \\
& + J_V\big[rV_t(1-\theta) + Q_t(\mu_t + D_t)\big] + \frac{1}{2}J_{WW}X_t^2\sigma_t^2 \\
& + \frac{1}{2}J_{VV}\frac{Q_t^2 p_D^2\omega^2 + \pi^2}{(1-\theta Q_t)^2} + J_{WV}\frac{X_t(Q_t p_D^2\omega^2 + \theta\pi^2)}{(1-\theta Q_t)^2}\Bigg\}.
\end{aligned} \tag{B.16}$$

The first-order conditions (FOCs) are

$$e^{-\delta t}U'(c_t^\star) = J_W, \tag{B.17}$$

$$X_t^\star = -\frac{J_W}{J_{WW}\sigma_t^2}(\mu_t - rP_t + D_t) - \frac{J_{WV}}{J_{WW}}\frac{Q_t p_D^2\omega^2 + \theta\pi^2}{(1-\theta Q_t)^2\sigma_t^2}. \tag{B.18}$$

As dynamic investors have CARA utility, I conjecture that the value function takes the form

$$J(W_t, V_t, t) = -e^{-\delta t - r\gamma W_t - g(V_t) - \beta} \tag{B.19}$$

Throughout the paper, subscripts on J denote partial derivatives. The partial derivatives of the value function are given by $J_t = -\delta J$, $J_W = -r\gamma J$, $J_{WW} = (r\gamma)^2 J$, $J_V = -g'(V_t)J$,

$J_{VV} = \big(g'(V_t)^2 - g''(V_t)\big)J$, and $J_{WV} = r\gamma g'(V_t)J$. Thus, the FOCs become

$$c_t^\star(W_t, V_t) = rW_t + \frac{1}{\gamma}\big(g(V_t) + \beta - \log r\big), \tag{B.20}$$

$$X_t^\star(P_t, D_t, V_t) = \frac{\mu_t - rP_t + D_t}{r\gamma\sigma_t^2} - \frac{g'(V_t)}{r\gamma}\frac{Q_t p_D^2\omega^2 + \theta\pi^2}{(1-\theta Q_t)^2\sigma_t^2}. \tag{B.21}$$

Since $J < 0$, the second-order condition is satisfied. At this stage, it is standard to substitute the FOCs and the market-clearing condition into the HJB. Most of the literature in this field assumes that $X_t = 1$. However, the presence of static investors complicates the problem, as the market clearing condition now requires $X_t + Q_t = 1$. By replacing the expression for Q_t into the market clearing condition,

$$X_t^\star = \frac{P_t - \theta V_t}{P_t}, \qquad Q_t = \frac{\theta V_t}{P_t}. \tag{B.22}$$

Substituting the conjectured equilibrium pricing function yields the following expressions.

$$X_t^\star = \frac{p_\gamma + p_D D_t + p_m m}{p_\gamma + p_D D_t + p_m m + \theta V_t}, \qquad Q_t = \frac{\theta V_t}{p_\gamma + p_D D_t + p_m m + \theta V_t}. \tag{B.23}$$

The equilibrium price must ensure consistency between the market clearing condition and the FOCs of the optimization program of the dynamic investors. Substituting the market clearing condition into the portfolio FOC and rearranging,

$$\mu_t - rP_t + D_t = r\gamma\sigma_t^2(1-Q_t) + g'(V_t)\frac{Q_t p_D^2\omega^2 + \theta\pi^2}{(1-\theta Q_t)^2}. \tag{B.24}$$

In the equilibrium without static investors of Lemma 1, $\theta = 0$, and the demand from dynamic investors equals the supply of stocks (see Veronesi, 1999). To solve for the general case with dynamic and static investors, I first examine the left-hand side of Equation (B.24). Substituting P_t and μ_t and rearranging terms,

$$\mu_t - rP_t + D_t = -\frac{1}{1-\theta Q_t} r p_\gamma. \tag{B.25}$$

Turning to the right-hand side of Equation (B.24), substituting σ_t^2 from Equation (B.7) yields

$$r\gamma\sigma_t^2(1-Q_t) + g'(V_t)\frac{Q_t p_D^2\omega^2 + \theta\pi^2}{(1-\theta Q_t)^2} = \frac{r\gamma(1-Q_t)(p_D^2\omega^2 + \theta^2\pi^2) + g'(V_t)(Q_t p_D^2\omega^2 + \theta\pi^2)}{(1-\theta Q_t)^2}. \tag{B.26}$$

Equating Equations (B.25) and (B.26) and multiplying both sides by $(1-\theta Q_t)^2$ yields

$$-rp_\gamma(1-\theta Q_t) = r\gamma(1-Q_t)(p_D^2\omega^2+\theta^2\pi^2) + g'(V_t)(Q_t p_D^2\omega^2+\theta\pi^2). \tag{B.27}$$

Both sides of Equation (B.27) are linear in Q_t, and the equality must hold for all states. Matching the constant terms,

$$-rp_\gamma = r\gamma(p_D^2\omega^2+\theta^2\pi^2) + g'(V_t)\theta\pi^2. \tag{B.28}$$

Matching the coefficients multiplying Q_t,

$$rp_\gamma\theta = -r\gamma(p_D^2\omega^2+\theta^2\pi^2) + g'(V_t)p_D^2\omega^2. \tag{B.29}$$

Adding θ times Equation (B.28) to Equation (B.29) yields

$$0 = r\gamma(1-\theta)(p_D^2\omega^2+\theta^2\pi^2) - g'(V_t)(p_D^2\omega^2+\theta^2\pi^2), \tag{B.30}$$

whose unique solution is $g'(V_t) = (1-\theta)r\gamma$, satisfied by the equation

$$g(V_t) = K + (1-\theta)r\gamma V_t, \tag{B.31}$$

for some constant K to be determined, which implies $g'(V_t) = (1-\theta)r\gamma$ and $g''(V_t) = 0$. Using Equations (B.7) and (B.31), the portfolio FOC becomes

$$X_t^\star = \frac{\mu_t - rP_t + D_t}{r\gamma\sigma_t^2} - (1-\theta)\frac{Q_t p_D^2\omega^2+\theta\pi^2}{p_D^2\omega^2+\theta^2\pi^2}. \tag{B.32}$$

Moreover, substituting Equation (B.31) back into Equation (B.28) yields

$$p_\gamma = -\gamma\left(\frac{\omega^2}{r^2}+\theta\pi^2\right), \tag{B.33}$$

which matches the definition of p_γ. Thus, the conjectured pricing function ensures that dynamic investors' FOC and the market clearing condition hold jointly. In Lemma 1, static investors are absent, $\theta = 0$, and the risk adjustment reduces to $p_g = -\gamma\frac{\omega^2}{r^2}$. In Proposition 1, static investors are present, and the compensation for risk, $p_\gamma = p_g + p_f$, incorporates the additional flow-risk adjustment, $p_f = -\gamma\theta\pi^2$.

To complete the verification, substitute $e^{-\delta t}U(c_t^\star)$ and $X_t^\star$ into the HJB.

$$\begin{aligned}0 &= \frac{1}{J}e^{-\delta t}U(c_t^\star) + \frac{1}{J}\frac{\mathbb{E}_t[dJ]}{dt} = r + \frac{1}{J}\frac{\mathbb{E}_t[dJ]}{dt} \\ &= r - \delta - r\gamma\left[\frac{1}{\gamma}(\log r - g(V_t) - \beta) + X_t^\star(\mu_t - rP_t + D_t)\right] + \frac{1}{2}(r\gamma)^2 X_t^{\star 2}\sigma_t^2 \\ &- g'(V_t)\big[rV_t(1-\theta) + Q_t(\mu_t + D_t)\big] + \frac{1}{2}g'(V_t)^2\frac{Q_t^2 p_D^2\omega^2 + \pi^2}{(1-\theta Q_t)^2} + r\gamma g'(V_t)\frac{X_t^\star(Q_t p_D^2\omega^2 + \theta\pi^2)}{(1-\theta Q_t)^2}.\end{aligned} \tag{B.34}$$

I have used the fact that $g''(V) = 0$. The portfolio FOC in Equation (B.21) implies that

$$r\gamma(\mu_t - rP_t + D_t) = (r\gamma)^2 X_t^\star\sigma_t^2 + r\gamma g'(V_t)\frac{Q_t p_D^2\omega^2 + \theta\pi^2}{(1-\theta Q_t)^2}. \tag{B.35}$$

Multiplying both sides of Equation (B.35) by $X_t^\star$ shows that the three terms involving $X_t^\star$ in Equation (B.34) combine into $-\frac{1}{2}(r\gamma X_t^\star\sigma_t)^2$. The HJB thus simplifies to

$$\begin{aligned}0 &= r - \delta - r(\log r - g(V_t) - \beta) - \frac{(r\gamma X_t^\star\sigma_t)^2}{2} \\ &- g'(V_t)\big[rV_t(1-\theta) + Q_t(\mu_t + D_t)\big] + \frac{g'(V_t)^2}{2}\frac{Q_t^2 p_D^2\omega^2 + \pi^2}{(1-\theta Q_t)^2}.\end{aligned} \tag{B.36}$$

Rewriting $Q_t(\mu_t + D_t) = Q_t(\mu_t - rP_t + D_t) + rQ_tP_t$ and using $rQ_tP_t = r\theta V_t$,

$$g'(V_t)\big[rV_t(1-\theta) + Q_t(\mu_t + D_t)\big] = (1-\theta)r\gamma\big[rV_t + Q_t(\mu_t - rP_t + D_t)\big]. \tag{B.37}$$

Substituting Equation (B.37) and $g(V_t) = K + (1-\theta)r\gamma V_t$ into the HJB Equation (B.36) yields

$$\begin{aligned}0 &= r - \delta - r\log r + rK + r\beta - \frac{(r\gamma)^2(1-Q_t)^2\sigma_t^2}{2} \\ &- (1-\theta)r\gamma Q_t(\mu_t - rP_t + D_t) + \frac{(1-\theta)^2 r^2\gamma^2}{2}\frac{Q_t^2 p_D^2\omega^2 + \pi^2}{(1-\theta Q_t)^2},\end{aligned} \tag{B.38}$$

which again uses $X_t^\star = 1 - Q_t$ from market clearing. Next, substituting σ_t^2 from Equation (B.7) and $\mu_t - rP_t + D_t$ from Equations (B.25) and (B.33), the terms in Q_t in Equation (B.38) collect as

$$-\frac{(r\gamma)^2}{2(1-\theta Q_t)^2}\Big(\big[p_D^2\omega^2 + (2\theta-1)\pi^2\big](1-\theta Q_t)^2\Big), \tag{B.39}$$

which simplifies to a constant term free of Q_t. Hence, Equation (B.38) reduces to

$$0 = r - \delta - r\log r + rK + r\beta - \frac{(r\gamma)^2}{2}\Big[p_D^2\omega^2 + (2\theta - 1)\pi^2\Big]. \tag{B.40}$$

After replacing $p_D = \frac{1}{r}$ and normalizing without loss of generality $\beta = \frac{(\gamma\omega)^2}{2r} + \frac{\delta}{r} + \log(r) - 1$, the HJB reduces to

$$0 = rK - \frac{r^2\gamma^2(2\theta - 1)\pi^2}{2}. \tag{B.41}$$

Thus, the guess satisfies the requisite FOC and market clearing conditions for $K = \frac{r\gamma^2(2\theta-1)\pi^2}{2}$. The transversality condition is also respected. Given Equation (B.19) and the wealth dynamics,

$$\lim_{h\to\infty} \mathbb{E}_t\Big[J(W_{t+h}, V_{t+h}, t+h)\Big] = \lim_{h\to\infty} \mathbb{E}_t\Big[-e^{-\delta(t+h) - r\gamma W_{t+h} - K - r\gamma(1-\theta)V_{t+h} - \beta}\Big] = 0. \tag{B.42}$$

This concludes the proof of Proposition 1. Lemma 1 follows as a special case when $\theta = 0$, which prevents static investors from allocating their wealth to equity assets. Q.E.D.

C The Stochastic Discount Factor

Proposition 1 is consistent with the SDF $M_t = e^{-\delta t}U'(c_t^\star)$. Equation (B.20) shows that the equilibrium consumption is

$$c_t^\star = rW_t + \frac{1}{\gamma}\big(g(V_t) + \beta - \log r\big). \tag{C.1}$$

With CARA utility, $U'(c_t) = \gamma e^{-\gamma c_t}$. Substituting the equilibrium consumption yields

$$M_t = \gamma r e^{-\delta t - r\gamma W_t - g(V_t) - \beta} = -\gamma r J. \tag{C.2}$$

As $g(V_t) = K + (1-\theta)r\gamma V_t$, the function $\log M_t$ is affine in W_t and V_t. Applying Itô's lemma,

$$d(\log M_t) = -\delta dt - r\gamma dW_t - (1-\theta)r\gamma dV_t. \tag{C.3}$$

Substituting Equations (3) and (5) evaluated at the equilibrium into Equation (C.3) yields

$$\begin{aligned} d(\log M_t) = &-\delta dt - r\gamma\Big[(rW_t - c_t^\star)dt + X_t^\star[(D_t - rP_t)dt + dP_t]\Big] \\ &- (1-\theta)r\gamma\Big[rV_t(1-\theta)dt + Q_t^\star(dP_t + D_t dt) + \pi dF_t\Big]. \end{aligned} \tag{C.4}$$

Collecting terms,

$$d(\log M_t) = \Big[-\delta - r\gamma[rW_t - c_t^\star + X_t^\star(D_t - rP_t)] - (1-\theta)r\gamma(rV_t(1-\theta) + Q_tD_t)\Big]dt \\ - r\gamma\big(X_t^\star + (1-\theta)Q_t\big)dP_t - (1-\theta)r\gamma\pi dF_t. \tag{C.5}$$

The market clearing condition implies that $X_t^\star + (1-\theta)Q_t = 1 - \theta Q_t$. Hence,

$$d(\log M_t) = \Big[-\delta - r\gamma[rW_t - c_t^\star + X_t^\star(D_t - rP_t)] - (1-\theta)r\gamma(rV_t(1-\theta) + Q_tD_t)\Big]dt \\ - r\gamma(1-\theta Q_t)dP_t - (1-\theta)r\gamma\pi dF_t. \tag{C.6}$$

Next, express the price dynamics in Equation (B.4) as follows.

$$(1-\theta Q_t)dP_t = p_D dD_t + \theta\big(rV_t(1-\theta) + Q_tD_t\big)dt + \theta\pi dF_t. \tag{C.7}$$

Substituting Equation (C.7) into (C.6) yields

$$d(\log M_t) = \Big[-\delta - r\gamma[rW_t - c_t^\star + X_t^\star(D_t - rP_t)] - (1-\theta)r\gamma(rV_t(1-\theta) + Q_tD_t)\Big]dt \\ - r\gamma\Big[p_D dD_t + \theta\big(r(1-\theta)V_t + Q_tD_t\big)dt + \theta\pi dF_t\Big] - (1-\theta)r\gamma\pi dF_t. \tag{C.8}$$

Collecting terms and substituting c_t^* from Equation (C.1),

$$d(\log M_t) = \Big[-\delta + r\big(g(V_t) + \beta - \log r\big) - r\gamma\big(X_t^\star(D_t - rP_t) + r(1-\theta)V_t + Q_tD_t\big)\Big]dt \\ - r\gamma p_D dD_t - r\gamma\pi dF_t. \tag{C.9}$$

Using the market clearing condition, $X_t^\star + Q_t = 1$, rewrite

$$X_t^\star(D_t - rP_t) + Q_tD_t = D_t - rP_t(1-Q_t) = (D_t - rP_t) + rP_tQ_t. \tag{C.10}$$

The static asset allocation policy, $Q_t = \theta V_t/P_t$, implies that $rP_tQ_t = r\theta V_t$. Hence,

$$X_t^\star(D_t - rP_t) + Q_tD_t = (D_t - rP_t) + r\theta V_t. \tag{C.11}$$

Substituting Equation (C.11) into (C.9) yields

$$d(\log M_t) = \Big[-\delta + r\big(g(V_t) + \beta - \log r\big) - r\gamma\big(D_t - rP_t + rV_t\big)\Big]dt \\ - r\gamma p_D dD_t - r\gamma\pi dF_t. \tag{C.12}$$

Recall that $p_D = 1/r$ and $dD_t = mdt + \omega dB_t$. Hence,

$$-r\gamma p_D dD_t = -\gamma dD_t = -\gamma m dt - \gamma\omega dB_t. \tag{C.13}$$

Thus, Equation (C.12) can be written as

$$d(\log M_t) = \Delta_t dt - \gamma\omega dB_t - \gamma r\pi dF_t, \tag{C.14}$$

where $\Delta_t = -\delta + r\big(g(V_t) + \beta - \log r\big) - r\gamma\big(D_t - rP_t + rV_t\big) - \gamma m$. Applying Itô's lemma to $M_t = \exp(\log M_t)$ yields

$$\frac{dM_t}{M_t} = \Big(\Delta_t + \tfrac{1}{2}\gamma^2\omega^2 + \tfrac{1}{2}\gamma^2 r^2\pi^2\Big)dt - \gamma\omega dB_t - \gamma r\pi dF_t. \tag{C.15}$$

Under the optimal policy, the HJB implies that

$$0 = e^{-\delta t}U(c_t^\star) + \frac{E_t[dJ]}{dt}. \tag{C.16}$$

Moreover,

$$e^{-\delta t}U(c_t^\star) = -\exp(-\delta t - \gamma c_t^\star) = -\exp(-\delta t - r\gamma W_t - g(V_t) - \beta + \log r) = rJ. \tag{C.17}$$

Thus,

$$\frac{1}{M_t}\frac{E_t[dM_t]}{dt} = \frac{1}{J}\frac{E_t[dJ]}{dt} = -r. \tag{C.18}$$

Comparing Equation (C.18) with Equation (C.15) implies that

$$\Delta_t + \frac{1}{2}(\gamma\omega)^2 + \tfrac{1}{2}(\gamma r\pi)^2 = -r. \tag{C.19}$$

Substituting Equation (C.19) into Equation (C.15) yields

$$\frac{dM_t}{M_t} = -rdt - \gamma\omega dB_t - \gamma r\pi dF_t. \tag{C.20}$$

The constant loadings on the risk factors represent the market prices of risk, denoted by

$$\lambda_B = \gamma\omega, \qquad \lambda_F = \gamma r\pi. \tag{C.21}$$

Equation (C.20) induces the risk-adjusted measure under which

$$dB_t^* = dB_t + \lambda_B dt, \qquad dF_t^* = dF_t + \lambda_F dt. \tag{C.22}$$

The absence of arbitrage in this intertemporal setting requires that the discounted cum-dividend stock market valuation is a discounted martingale under the risk-adjusted measure, so that

$$E_t^*[dP_t + D_t dt] = rP_t dt. \tag{C.23}$$

Since $dD_t = mdt + \omega dB_t$, Equation (C.22) implies

$$dD_t = (m - \omega\lambda_B)dt + \omega dB_t^* = (m - \gamma\omega^2)dt + \omega dB_t^*. \tag{C.24}$$

Hence, for $s \geq t$,

$$E_t^*[D_s] = D_t + (m - \gamma\omega^2)(s - t). \tag{C.25}$$

Therefore,

$$\begin{aligned} E_t^*\left[\int_t^\infty e^{-r(s-t)} D_s ds\right] &= \int_t^\infty e^{-r(s-t)} \left(D_t + (m - \gamma\omega^2)(s-t)\right) ds \\ &= \frac{D_t}{r} + \frac{m - \gamma\omega^2}{r^2}. \end{aligned} \tag{C.26}$$

The implied risk adjustment to the discounted dividend claim is

$$p_g = -\gamma \frac{\omega^2}{r^2}. \tag{C.27}$$

From the law of motion for V_t,

$$dV_t = rV_t(1 - \theta)dt + Q_t(dP_t + D_t dt) + \pi dF_t. \tag{C.28}$$

From Equation (C.22),

$$E_t^*[\pi dF_t] = \pi E_t^*[dF_t^* - \lambda_F dt] = -\pi\lambda_F dt = -\gamma r\pi^2 dt. \tag{C.29}$$

Hence,

$$E_t^*[dV_t] = rV_t(1 - \theta)dt + Q_t rP_t dt - \gamma r\pi^2 dt = (rV_t - \gamma r\pi^2)dt. \tag{C.30}$$

Next, using the affine equilibrium price representation established in Proposition 1,

$$dP_t = p_D dD_t + \theta dV_t. \tag{C.31}$$

Evaluating the risk-adjusted expectation of the above Equation (C.31), and using Equations (C.24) and (C.30), yields

$$E_t^*[dP_t] = \left[p_D(m - \gamma\omega^2) + \theta(rV_t - \gamma r\pi^2)\right] dt. \tag{C.32}$$

Substituting Equation (C.32) into Equation (C.23) yields

$$p_D(m - \gamma\omega^2) + \theta(rV_t - \gamma r\pi^2) + D_t = rP_t. \tag{C.33}$$

Using $p_D = \frac{1}{r}$, $p_g = -\gamma\frac{\omega^2}{r^2}$, and $p_f = -\gamma\theta\pi^2$, and rearranging terms,

$$P_t = p_g + \frac{m}{r^2} + \frac{D_t}{r} + p_f + \theta V_t. \tag{C.34}$$

Thus, the SDF approach reproduces the equilibrium stock market valuation of Proposition 1. Furthermore, it allows one to determine the market prices of the risk factors.

D Proof of Remark 1

In the absence of arbitrage opportunities, the risk-adjusted expected return on stocks coincides with the rate of return on the risk-free asset. Thus, under the risk-adjusted measure, the conditional expectation of static investors' wealth dynamics in Equation (5) is

$$\mathbb{E}_t^*[dV_t] = rV_t dt + \mathbb{E}_t^*[\pi dF_t]. \tag{D.1}$$

Multiplying both sides of Equation (D.1) by the constant θ preserves the equality. Namely,

$$\mathbb{E}_t^*[d\theta V_t] = r\theta V_t dt + \theta\mathbb{E}_t^*[\pi dF_t]. \tag{D.2}$$

From Equation (C.29), it follows that

$$p_f = \frac{\theta}{r}\frac{\mathbb{E}_t^*[\pi dF_t]}{dt}. \tag{D.3}$$

Substituting Equation (D.3) into Equation (D.2),

$$\mathbb{E}_t^*[d\theta V_t] = r(\theta V_t + p_f)dt. \tag{D.4}$$

Hence, for every positive time horizon h,

$$p_f + \theta V_t = e^{-rh}\mathbb{E}_t^*[p_f + \theta V_{t+h}]. \tag{D.5}$$

Equation (D.5) characterizes a discounted martingale under the risk-adjusted measure. Q.E.D.

E Stock Market Valuation Dynamics

The valuation of the equity asset class characterized in Proposition 1 follows the dynamics

$$dP_t = p_D dD_t + \theta dV_t. \tag{E.1}$$

Asset price dynamics are driven by the evolution of dividends and the wealth of static investors. By replacing Equation (5) in the above expression,

$$dP_t = p_D dD_t + \theta\big[rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi dF_t\big]. \tag{E.2}$$

From Equation (E.2), it is observed that the equity holdings of static investors, Q_t, give rise to price amplification effects.[23] The intuition for this effect is as follows. Changes in stock market valuation, dP_t, affect the wealth of both dynamic and static investors. Static investors retain a proportion θ of their capital gains in the equity asset class, increasing their target dollar exposure to equities and the resulting price pressure. This may be surprising, as static investors rebalance their portfolio in the opposite direction of price changes. As an illustration, consider the following example.

Example 1. Suppose $P_t = \$100$, $\theta V_t = \$50$, $X_t = Q_t = 0.5$, $\theta = 0.4$. As firms report earnings, the present value of the dividend stream increases by \$20. Dynamic investors increase their equity demand and stock market valuation rises to $P_t + dP_t = \$120$. Dynamic investors experience capital gains $dW_t = X_t dP_t = \$10$ and realize them to increase consumption. Static investors experience unrealized capital gains $dV_t = Q_t dP_t = \$10$. As static investors' equity exposure rises, the stock market valuation rises to \$130. Equities become overweight in static investors' portfolio, and they rebalance $(1-\theta)dV_t = \$6$ away from stocks, leading to a stock market valuation of \$124. Equities become slightly underweight, prompting further investment. This process leads to an amplification of $\frac{1}{1-\theta Q_t} = 1.25$. In the new equilibrium, $P_t = \$125$, $\theta V_t = \$55$, $X_t = 0.56$, and $Q_t = 0.44$. After news of a \$20 increase in the present value of dividends, the stock market valuation rises by \$25. Absent static investors, it would have risen by \$20.

Harvey et al. (2025) documented that predictable rebalancing trades by institutional investors adhering to static asset allocation strategies exert a temporary impact on the aggregate returns on the stock market. In Example 1, the price pressure from portfolio rebalancing corresponds

[23] This wealth amplification effect shares similarities with Basak and Pavlova (2013), while stemming from a different group of investors; namely, institutional investors following static asset allocation strategies. The amplification effect requires the demand pressure generated by static investors to dominate the wealth effect operating through dynamic investors' portfolio choice, which is muted under CARA utility. Thus, whether static investors give rise to wealth amplification effects depends in general on the utility function of dynamic investors.

to the downward pressure exerted by static investors' sales after they become overweight in equities. The temporary nature of this effect is consistent with the model, as rebalancing restores portfolio weights without altering the level of wealth invested under static strategies. On the other hand, the price pressure exerted by static investors also exhibits a persistent component that reflects their continued capital allocation to the stock market. In Example 1, the equity exposure of static investors rises from \$50 to \$55 after the shock, corresponding to a persistent \$5 increment in the stock market valuation.

Hartzmark and Solomon (2025) document that dividend payments generate aggregate market-wide price pressure that does not reverse over the subsequent month. This evidence is puzzling, as the amount and timing of dividends have already been announced to the market ahead of the payment date. The price process in Equation (E.2) offers a potential explanation. In the model, dividend payments generate price pressure because static investors reinvest a preset fraction of received dividends into the equity asset class, creating upward pressure on aggregate stock prices at the time of distribution. Of course, dynamic investors may also reinvest part of their capital gains in response to a positive wealth shock. However, absent binding borrowing constraints, anticipated dividends should lead dynamic investors to adjust their portfolios as soon as the future dividend is announced, rather than at the time of the dividend distribution. The timing of the price pressure is thus more naturally explained by the presence of static investors.

F General Preferences of Dynamic Investors

This section examines the robustness of the asset classification effect to the preferences of dynamic investors. The only restriction on the preferences of dynamic investors is that they induce a well-defined SDF, denoted by M_t. The evolution of this SDF is given by

$$\frac{dM_t}{M_t} = -rdt - \lambda_t^B dB_t - \lambda_t^F dF_t, \tag{F.1}$$

where λ_t^B and λ_t^F are the equilibrium prices of dividend risk and flow risk. These prices of risk can assume different functional forms, depending on the preferences of dynamic investors, and may in general depend on the state variables. The CARA environment in Proposition 1 corresponds to the particular case in which the market prices of risk are constant.

First, consider an economy solely populated by dynamic investors. As the stock market portfolio is in unit supply, market clearing requires $X_t = 1$. No-arbitrage requires the stock market gain process, discounted by M_t, to evolve as a martingale. Thus, under the risk-adjusted measure induced by M_t,

$$E_t^*[dP_t + D_t dt] = rP_t dt. \tag{F.2}$$

Hence, for any $T > t$,

$$P_t = E_t^* \left[\int_t^T e^{-r(s-t)} D_s ds + e^{-r(T-t)} P_T \right]. \tag{F.3}$$

Assume, as in Remark 3, that dynamic investors' equity holdings satisfy

$$\lim_{T \to \infty} E_t^* \left[e^{-r(T-t)} X_T P_T \right] = 0. \tag{F.4}$$

In the benchmark economy without static investors, dynamic investors hold the entire stock supply, so market clearing requires $X_T = 1$. The additional terminal condition on their equity holdings therefore reduces to the standard transversality condition on the stock price,

$$\lim_{T \to \infty} E_t^* \left[e^{-r(T-t)} P_T \right] = 0, \tag{F.5}$$

so that

$$P_t = PDV_t \equiv E_t^* \left[\int_t^\infty e^{-r(s-t)} D_s ds \right]. \tag{F.6}$$

Throughout this section, PDV_t denotes the present discounted value of the dividend stream under the SDF of dynamic investors in the economy under consideration. Thus, Equation (F.6) extends Lemma 1 to the case in which dynamic investors have arbitrary preferences inducing a well-defined SDF.

Second, consider an economy with both dynamic and static investors. In this economy, static investors allocate a preset fraction of their wealth to the stock market,

$$Q_t = \theta V_t / P_t. \tag{F.7}$$

Market clearing requires

$$X_t + Q_t = 1. \tag{F.8}$$

Combining Equations (F.7) and (F.8),

$$X_t P_t = P_t - \theta V_t. \tag{F.9}$$

Static investors' wealth evolves according to

$$dV_t = r V_t dt + Q_t \left[(D_t - r P_t) dt + dP_t \right] + \pi dF_t. \tag{F.10}$$

Using Equation (F.2), the stock excess payoff has zero expected value under the risk-adjusted

measure induced by the preferences of dynamic investors.[24]

$$E_t^*\Big[(D_t - rP_t)dt + dP_t\Big] = 0. \tag{F.11}$$

By Girsanov's theorem, under the risk-adjusted measure,

$$E_t^*[dF_t] = -\lambda_t^F dt. \tag{F.12}$$

Therefore,

$$E_t^*[dV_t] = rV_t dt - \pi\lambda_t^F dt. \tag{F.13}$$

Multiplying the above expression by θ and integrating forward until time T yields

$$\theta V_t = E_t^*\left[e^{-r(T-t)}\theta V_T + \int_t^T e^{-r(s-t)}\theta\pi\lambda_s^F ds\right]. \tag{F.14}$$

By no-arbitrage, the aggregate valuation of the stock market satisfies

$$P_t = E_t^*\left[\int_t^T e^{-r(s-t)}D_s ds + e^{-r(T-t)}P_T\right]. \tag{F.15}$$

Subtracting Equation (F.14) from Equation (F.15) yields

$$P_t - \theta V_t = E_t^*\left[\int_t^T e^{-r(s-t)}\Big(D_s - \theta\pi\lambda_s^F\Big)ds + e^{-r(T-t)}(P_T - \theta V_T)\right]. \tag{F.16}$$

Using Equation (F.9),

$$X_t P_t = E_t^*\left[\int_t^T e^{-r(s-t)}\Big(D_s - \theta\pi\lambda_s^F\Big)ds + e^{-r(T-t)}X_T P_T\right]. \tag{F.17}$$

Taking the limit as $T \to \infty$ in Equation (F.17) and using Equation (F.4) yields

$$X_t P_t = E_t^*\left[\int_t^\infty e^{-r(s-t)}\Big(D_s - \theta\pi\lambda_s^F\Big)ds\right]. \tag{F.18}$$

In the economy with both dynamic and static investors, let

$$PDV_t = E_t^*\left[\int_t^\infty e^{-r(s-t)}D_s ds\right], \tag{F.19}$$

where the expected value is computed under the SDF of dynamic investors in this economy.

[24] The SDF induced by any given preferences of dynamic investors may differ across the economy with only dynamic investors and the economy with both dynamic and static investors, as state variables and dynamic investors' optimal policies may differ across the two economies.

Moreover, define the flow-risk adjustment as follows.

$$p_{f,t} = -E_t^* \left[\int_t^\infty e^{-r(s-t)} \theta \pi \lambda_s^F ds \right]. \tag{F.20}$$

Thus, substituting these definitions into Equation (F.18),

$$X_t P_t = PDV_t + p_{f,t}. \tag{F.21}$$

From Equation (F.9),

$$P_t = \underbrace{\text{PDV}_t}_{Fundamentals} + \underbrace{p_{f,t} + \theta V_t}_{Asset\ Classification\ Effect} \tag{F.22}$$

Thus, in general, the present value of the dividend stream reflects the preferences of dynamic investors via their required discount rates. Moreover, the asset classification effect is given by

$$p_{f,t} + \theta V_t. \tag{F.23}$$

The term θV_t follows from static investors' asset allocation strategy and market clearing, and does not depend on the preferences of dynamic investors. The term $p_{f,t}$ is the present value, evaluated under the SDF induced by dynamic investors' preferences, of the flow-risk adjustment motivated by the exposure of stock market valuation to wealth flows, dF_t.

The specific utility function of dynamic investors shapes the market price of earnings risk, λ_t^B, which affects the present value of the dividend stream, PDV_t. Dynamic investors' utility function determines the market price of flow risk, λ_t^F, and thus the flow risk-adjustment $p_{f,t}$, but does not influence the additive term θV_t. In conclusion, the decomposition in Equation (F.22) holds under general preferences of dynamic investors, and the θV_t component of the asset classification effect is independent of their specific utility function.

G Proof of Corollary 2

From Equation (B.6), the drift coefficient of the stock market valuation is

$$\mu_t = \frac{\frac{m}{r} + \theta[rV_t(1-\theta) + Q_t D_t]}{1 - \theta Q_t}. \tag{G.1}$$

The associated expected instantaneous total return is

$$\mathbb{E}_t \left[\frac{dP_t + D_t dt}{P_t} \right] = \frac{\mu_t + D_t}{P_t} dt. \tag{G.2}$$

Substituting $\theta V_t = Q_t P_t$ yields

$$\mathbb{E}_t\left[\frac{dP_t + D_t dt}{P_t}\right] = \frac{\frac{m}{r} + D_t + rQ_tP_t(1-\theta)}{P_t(1-\theta Q_t)}dt. \tag{G.3}$$

From Proposition 1, $P_t(1-Q_t) = p_\gamma + \frac{D_t}{r} + \frac{m}{r^2}$, so that $\frac{m}{r} + D_t = rP_t(1-Q_t) - rp_\gamma$. Substituting this expression yields

$$\frac{m}{r} + D_t + rQ_tP_t(1-\theta) = rP_t(1-\theta Q_t) - rp_\gamma. \tag{G.4}$$

Thus,

$$\mathbb{E}_t\left[\frac{dP_t + D_t dt}{P_t}\right] = r\left[1 - \frac{p_\gamma(1-Q_t)}{(p_\gamma + \frac{D_t}{r} + \frac{m}{r^2})(1-\theta Q_t)}\right]dt. \tag{G.5}$$

Differentiating with respect to Q_t,

$$\frac{\partial}{\partial Q_t}\mathbb{E}_t\left[\frac{dP_t + D_t dt}{P_t}\right] = -\frac{rp_\gamma}{p_\gamma + \frac{D_t}{r} + \frac{m}{r^2}}\frac{\theta - 1}{(1-\theta Q_t)^2}dt < 0. \tag{G.6}$$

The inequality follows from $p_\gamma < 0$, $p_\gamma + \frac{D_t}{r} + \frac{m}{r^2} = P_t(1-Q_t) > 0$, and $\theta \in [0,1)$. Q.E.D.

H Proof of Proposition 2

Conjecture that the price of the i-th stock is given by the following expression.

$$P_{it} = p_{\gamma_i} + p_D D_{it} + p_m m_i + p^A_{f_{it}} + p^P_{f_{it}} + \theta\left[q^\star_{it}V^A_t + \lambda_{it}V^P_t\right], \tag{H.1}$$

where

$$p^A_{fit} = -\gamma\theta\pi\pi^A q^\star_{it}, \qquad p^P_{fit} = -\gamma\theta\pi\pi^P\lambda_{it}. \tag{H.2}$$

For convenience, let $p_{fit} = p^A_{fit} + p^P_{fit}$. It will be shown that Equation (H.1) is an equivalent representation of the pricing function in Proposition 2. The portfolio weights of index trackers are given by

$$\lambda_{it} = P_{it}N_i/P^{\text{IDX}}_t. \tag{H.3}$$

Dividing the objective function in Equation (27) by dt, stock pickers choose $\{Q^A_{it}\}_{i=1}^I$ to solve:

$$\max_{\{Q^A_{it}\}}\left\{\sum_{i=1}^I Q^A_{it}(\mu_{it} + D_{it}) - \frac{\gamma}{2}\sum_{i=1}^I\sum_{j=1}^I Q^A_{it}Q^A_{jt}\sigma_{ijt}\right\} \tag{H.4}$$

subject to:

$$\sum_{i=1}^I Q^A_{it}P_{it} = \theta V^A_t. \tag{H.5}$$

The associated Lagrangian function is:

$$\mathcal{L} = \sum_{i=1}^{I} Q_{it}^{A}(\mu_{it} + D_{it}) - \frac{\gamma}{2}\sum_{i=1}^{I}\sum_{j=1}^{I} Q_{it}^{A} Q_{jt}^{A}\sigma_{ijt} - \xi_t\left(\sum_{i=1}^{I} Q_{it}^{A} P_{it} - \theta V_t^{A}\right). \tag{H.6}$$

The FOCs are:

$$\frac{\partial \mathcal{L}}{\partial Q_{it}^{A}} = (\mu_{it} + D_{it}) - \gamma\sum_{j=1}^{I} Q_{jt}^{A}\sigma_{ijt} - \xi_t P_{it} = 0. \tag{H.7}$$

Rearranging terms,

$$Q_{it}^{A\star} = \frac{\mu_{it} - \xi_t P_{it} + D_{it}}{\gamma\sigma_{it}^{2}} - \sum_{j\neq i}\frac{Q_{jt}^{A\star}\sigma_{ijt}}{\sigma_{it}^{2}}, \tag{H.8}$$

where ξ_t is a Lagrange multiplier on Equation (H.5).

Stock pickers' problem can alternatively be formulated in terms of equity-sleeve weights. Let R_t be the vector of expected returns on the I stocks, Σ_t be the covariance matrix of their returns, $\mathbf{1}$ be an $I \times 1$ vector of ones, and q_t be an $I \times 1$ vector of within-equity portfolio weights. As the dollar value of their equity sleeve is θV_t^{A}, stock pickers solve

$$\max_{q_t}\left\{q_t^{\top} R_t - \frac{\gamma\theta V_t^{A}}{2} q_t^{\top}\Sigma_t q_t\right\} \quad \text{s.t. } \mathbf{1}^{\top} q_t = 1. \tag{H.9}$$

For notational convenience, define $\widetilde{\gamma}_t = \gamma\theta V_t^{A}$. The Lagrangian function is

$$\mathcal{L}(q_t, \chi_t) = q_t^{\top} R_t - \frac{\widetilde{\gamma}_t}{2} q_t^{\top}\Sigma_t q_t - \chi_t\big(\mathbf{1}^{\top} q_t - 1\big). \tag{H.10}$$

The FOC with respect to the vector q_t is

$$R_t - \widetilde{\gamma}_t\Sigma_t q_t - \chi_t\mathbf{1} = 0, \tag{H.11}$$

which implies that

$$q_t^{\star} = \frac{1}{\widetilde{\gamma}_t}\Sigma_t^{-1}\big(R_t - \chi_t\mathbf{1}\big). \tag{H.12}$$

Imposing the constraint $\mathbf{1}^{\top} q_t = 1$ yields the expression for the Lagrange multiplier χ_t,

$$\chi_t = \frac{\mathbf{1}^{\top}\Sigma_t^{-1} R_t - \widetilde{\gamma}_t}{\mathbf{1}^{\top}\Sigma_t^{-1}\mathbf{1}}. \tag{H.13}$$

Substituting Equation (H.13) into (H.12), the optimal within-equity weights are

$$q_t^{\star} = \frac{1}{\widetilde{\gamma}_t}\Sigma_t^{-1} R_t - \frac{1}{\widetilde{\gamma}_t}\left(\frac{\mathbf{1}^{\top}\Sigma_t^{-1} R_t - \widetilde{\gamma}_t}{\mathbf{1}^{\top}\Sigma_t^{-1}\mathbf{1}}\right)\Sigma_t^{-1}\mathbf{1}. \tag{H.14}$$

The portfolio weights of stock pickers, $q_{it}^{\star}$, are obtained from the mean-variance problem above. Index trackers hold the index weights λ_{it}. Hence, the number of shares of stock i held by static investors is

$$Q_{it} = Q_{it}^{A} + Q_{it}^{P} = \frac{\theta q_{it}^{\star} V_t^{A}}{P_{it}} + \frac{\theta \lambda_{it} V_t^{P}}{P_{it}}. \tag{H.15}$$

Since each stock is in unit supply, stock-level market clearing requires

$$X_{it}^{\star} + Q_{it} = 1. \tag{H.16}$$

Before turning to dynamic investors' optimization program, let $\mathbf{P}_t$, $\mathbf{D}_t$, $\boldsymbol{\mu}_t$, $\mathbf{X}_t$, and $\mathbf{Q}_t$ denote the vectors of individual stock prices, dividends, price drifts, dynamic investors' holdings, and static investors' holdings. Let Ω_t denote the covariance matrix of stock price changes, whose (i, j) element is σ_{ijt}. Define the vector of excess stock payoffs by

$$d\mathbf{Y}_t = (\mathbf{D}_t - r\mathbf{P}_t)dt + d\mathbf{P}_t. \tag{H.17}$$

Let its conditional mean be denoted by

$$\overline{\mathbf{Y}}_t = \frac{\mathbb{E}_t[d\mathbf{Y}_t]}{dt} = \boldsymbol{\mu}_t - r\mathbf{P}_t + \mathbf{D}_t. \tag{H.18}$$

With this notation in place, the wealth of dynamic investors evolves as

$$dW_t = (rW_t - c_t)dt + \mathbf{X}_t^{\top} d\mathbf{Y}_t. \tag{H.19}$$

The wealth of static investors evolves as

$$dV_t = rV_t(1-\theta)dt + \mathbf{Q}_t^{\top}(d\mathbf{P}_t + \mathbf{D}_t dt) + \pi dF_t. \tag{H.20}$$

The requirement that static investors allocate the dollar amount θV_t to equities is

$$\mathbf{Q}_t^{\top}\mathbf{P}_t = \theta V_t. \tag{H.21}$$

Combining Equations (H.20) and (H.21),

$$\frac{\mathbb{E}_t[dV_t]}{dt} = rV_t + \mathbf{Q}_t^{\top}\overline{\mathbf{Y}}_t. \tag{H.22}$$

Similarly,

$$\frac{\mathbb{E}_t[dW_t]}{dt} = rW_t - c_t + \mathbf{X}_t^{\top}\overline{\mathbf{Y}}_t. \tag{H.23}$$

The quadratic variation of dynamic investors' wealth is

$$\frac{\mathbb{E}_t[dW_t^2]}{dt} = \mathbf{X}_t^\top \Omega_t \mathbf{X}_t. \tag{H.24}$$

Let

$$\boldsymbol{\kappa}_t = \frac{\mathrm{Cov}_t(d\mathbf{P}_t, dV_t)}{dt}. \tag{H.25}$$

Then,

$$\frac{\mathbb{E}_t[dW_t dV_t]}{dt} = \mathbf{X}_t^\top \boldsymbol{\kappa}_t. \tag{H.26}$$

Finally, define

$$\nu_t = \frac{\mathbb{E}_t[dV_t^2]}{dt}. \tag{H.27}$$

As in Appendix B, conjecture that dynamic investors' value function is

$$J(W_t, V_t, t) = -e^{-\delta t - r\gamma W_t - g(V_t) - \beta}, \tag{H.28}$$

where

$$g(V_t) = K + (1-\theta) r\gamma V_t. \tag{H.29}$$

The partial derivatives of the value function are again given by $J_t = -\delta J$, $J_W = -r\gamma J$, $J_{WW} = (r\gamma)^2 J$, $J_V = -g'(V_t)J$, $J_{VV} = \big(g'(V_t)^2 - g''(V_t)\big)J$, and $J_{WV} = r\gamma g'(V_t) J$.

The HJB equation is

$$\begin{aligned} 0 = \max_{\{c_t, \mathbf{X}_t\}} \Bigg\{ & e^{-\delta t} U(c_t) + J_t + J_W \frac{\mathbb{E}_t[dW_t]}{dt} + J_V \frac{\mathbb{E}_t[dV_t]}{dt} + \frac{1}{2} J_{WW} \frac{\mathbb{E}_t[dW_t^2]}{dt} \\ & + \frac{1}{2} J_{VV} \frac{\mathbb{E}_t[dV_t^2]}{dt} + J_{WV} \frac{\mathbb{E}_t[dW_t dV_t]}{dt} \Bigg\}. \end{aligned} \tag{H.30}$$

The FOC for consumption is

$$e^{-\delta t} U'(c_t^\star) = J_W. \tag{H.31}$$

Therefore,

$$c_t^\star = r W_t + \frac{g(V_t) + \beta - \log r}{\gamma}. \tag{H.32}$$

Using Equation (H.31),

$$\frac{1}{J} e^{-\delta t} U(c_t^\star) = r. \tag{H.33}$$

The FOC with respect to the vector $\mathbf{X}_t$ is

$$J_W \overline{\mathbf{Y}}_t + J_{WW} \Omega_t \mathbf{X}_t + J_{WV} \boldsymbol{\kappa}_t = 0. \tag{H.34}$$

Substituting the partial derivatives of the value function into Equation (H.34) yields

$$\overline{\mathbf{Y}}_t = r\gamma\Omega_t\mathbf{X}_t^\star + (1-\theta)r\gamma\boldsymbol{\kappa}_t. \tag{H.35}$$

This equation is the matrix analogue of the FOC in Equation (B.21). Component by component, Equation (H.35) yields

$$X_{it}^\star = \frac{\mu_{it} - rP_{it} + D_{it}}{r\gamma\sigma_{it}^2} - \frac{\sum_{j\neq i} X_{jt}^\star\sigma_{ijt}}{\sigma_{it}^2} - \frac{(1-\theta)}{\sigma_{it}^2}\frac{\mathrm{Cov}_t(dP_{it}, dV_t)}{dt}. \tag{H.36}$$

Since $J < 0$ and Ω_t is positive definite, the second-order condition is satisfied. It remains to verify the HJB. Substituting Equations (H.22) – (H.27) and the partial derivatives of the value function into Equation (H.30), evaluating at $c_t^\star$ and $\mathbf{X}_t^\star$, and dividing by J, yields

$$\begin{aligned} 0 =& r - \delta - r\big\{\log r - g(V_t) - \beta\big\} - r\gamma\mathbf{X}_t^{\star\top}\overline{\mathbf{Y}}_t - (1-\theta)r\gamma\big\{rV_t + \mathbf{Q}_t^\top\overline{\mathbf{Y}}_t\big\} \\ &+ \frac{(r\gamma)^2}{2}\mathbf{X}_t^{\star\top}\Omega_t\mathbf{X}_t^\star + \frac{(1-\theta)^2r^2\gamma^2}{2}\nu_t + (1-\theta)r^2\gamma^2\mathbf{X}_t^{\star\top}\boldsymbol{\kappa}_t. \end{aligned} \tag{H.37}$$

Using Equation (H.29) to cancel out the terms in V_t yields

$$\begin{aligned} 0 =& r - \delta - r\log r + rK + r\beta - r\gamma\mathbf{X}_t^{\star\top}\overline{\mathbf{Y}}_t - (1-\theta)r\gamma\mathbf{Q}_t^\top\overline{\mathbf{Y}}_t \\ &+ \frac{(r\gamma)^2}{2}\mathbf{X}_t^{\star\top}\Omega_t\mathbf{X}_t^\star + \frac{(1-\theta)^2r^2\gamma^2}{2}\nu_t + (1-\theta)r^2\gamma^2\mathbf{X}_t^{\star\top}\boldsymbol{\kappa}_t. \end{aligned} \tag{H.38}$$

Premultiplying Equation (H.35) by $\mathbf{X}_t^{\star\top}$ yields

$$\mathbf{X}_t^{\star\top}\overline{\mathbf{Y}}_t = r\gamma\mathbf{X}_t^{\star\top}\Omega_t\mathbf{X}_t^\star + (1-\theta)r\gamma\mathbf{X}_t^{\star\top}\boldsymbol{\kappa}_t. \tag{H.39}$$

Premultiplying Equation (H.35) by $\mathbf{Q}_t^\top$ yields

$$\mathbf{Q}_t^\top\overline{\mathbf{Y}}_t = r\gamma\mathbf{Q}_t^\top\Omega_t\mathbf{X}_t^\star + (1-\theta)r\gamma\mathbf{Q}_t^\top\boldsymbol{\kappa}_t. \tag{H.40}$$

Substituting Equations (H.39) and (H.40) into Equation (H.38),

$$\begin{aligned} 0 =& r - \delta - r\log r + rK + r\beta - \frac{(r\gamma)^2}{2}\big(\mathbf{X}_t^\star + (1-\theta)\mathbf{Q}_t\big)^\top\Omega_t\big(\mathbf{X}_t^\star + (1-\theta)\mathbf{Q}_t\big) \\ &+ \frac{(1-\theta)^2r^2\gamma^2}{2}\big(\nu_t - 2\mathbf{Q}_t^\top\boldsymbol{\kappa}_t + \mathbf{Q}_t^\top\Omega_t\mathbf{Q}_t\big). \end{aligned} \tag{H.41}$$

To simplify this expression, notice that $\mathbf{Q}_t$ is known at time t. Hence,

$$\begin{aligned}\frac{1}{dt}\mathbb{E}_t\Big[(dV_t - \mathbf{Q}_t^\top d\mathbf{P}_t)^2\Big] &= \frac{1}{dt}\mathbb{E}_t[dV_t^2] - 2\mathbf{Q}_t^\top \frac{1}{dt}\mathbb{E}_t[d\mathbf{P}_t dV_t] + \mathbf{Q}_t^\top \frac{1}{dt}\mathbb{E}_t[d\mathbf{P}_t d\mathbf{P}_t^\top]\mathbf{Q}_t \\ &= \nu_t - 2\mathbf{Q}_t^\top \boldsymbol{\kappa}_t + \mathbf{Q}_t^\top \Omega_t \mathbf{Q}_t. \end{aligned} \tag{H.42}$$

This equality follows from the definitions of ν_t, $\boldsymbol{\kappa}_t$, and Ω_t. Moreover, from Equation (H.20),

$$dV_t - \mathbf{Q}_t^\top d\mathbf{P}_t = [rV_t(1-\theta) + \mathbf{Q}_t^\top \mathbf{D}_t]dt + \pi dF_t. \tag{H.43}$$

Therefore,

$$\frac{1}{dt}\mathbb{E}_t\Big[(dV_t - \mathbf{Q}_t^\top d\mathbf{P}_t)^2\Big] = \pi^2. \tag{H.44}$$

Combining Equations (H.42) and (H.44) yields

$$\nu_t - 2\mathbf{Q}_t^\top \boldsymbol{\kappa}_t + \mathbf{Q}_t^\top \Omega_t \mathbf{Q}_t = \pi^2. \tag{H.45}$$

Moreover, the market clearing condition for all stocks,

$$\mathbf{X}_t^\star + \mathbf{Q}_t = \mathbf{1}, \tag{H.46}$$

implies that

$$\mathbf{X}_t^\star + (1-\theta)\mathbf{Q}_t = \mathbf{1} - \theta\mathbf{Q}_t. \tag{H.47}$$

Substituting Equations (H.45) and (H.47) into Equation (H.41) yields

$$0 = r - \delta - r\log r + rK + r\beta - \frac{(r\gamma)^2}{2}(\mathbf{1} - \theta\mathbf{Q}_t)^\top \Omega_t (\mathbf{1} - \theta\mathbf{Q}_t) + \frac{(1-\theta)^2 r^2 \gamma^2 \pi^2}{2}. \tag{H.48}$$

Summing the conjectured prices in Equation (H.1) across stocks yields

$$\mathbf{1}^\top \mathbf{P}_t = p_g + p_D D_t + p_m m + p_f + \theta V_t = P_t. \tag{H.49}$$

From Equation (H.49),

$$\mathbf{1}^\top d\mathbf{P}_t = p_D dD_t + \theta dV_t. \tag{H.50}$$

Substituting Equation (H.20) and rearranging terms,

$$\big(\mathbf{1} - \theta\mathbf{Q}_t\big)^\top d\mathbf{P}_t = p_D dD_t + \theta\pi dF_t + \theta\big[rV_t(1-\theta) + \mathbf{Q}_t^\top \mathbf{D}_t\big]dt. \tag{H.51}$$

The last term is predictable at time t and does not contribute to conditional second moments.

Hence,

$$(\mathbf{1} - \theta \mathbf{Q}_t)^\top \Omega_t (\mathbf{1} - \theta \mathbf{Q}_t) = \frac{1}{dt} \mathbb{E}_t[(p_D dD_t + \theta \pi dF_t)^2] = p_D^2 \omega^2 + \theta^2 \pi^2. \tag{H.52}$$

The last equality uses the definition of Ω_t as the covariance matrix of stock price changes. Substituting Equation (H.52) into Equation (H.48) yields

$$0 = r - \delta - r \log r + rK + r\beta - \frac{\gamma^2 \omega^2}{2} - \frac{r^2 \gamma^2 (2\theta - 1)\pi^2}{2}. \tag{H.53}$$

Using the constants from Appendix B,

$$\beta = \frac{\gamma^2 \omega^2}{2r} + \frac{\delta}{r} + \log r - 1, \tag{H.54}$$

and

$$K = \frac{r\gamma^2 (2\theta - 1)\pi^2}{2}, \tag{H.55}$$

Equation (H.53) is equal to zero. Hence, the conjectured value function satisfies the HJB.

It remains to show that Equation (31) corresponds to the expression in Proposition 2. Using Equation (22) to replace the dividends process,

$$\mathbb{E}_t \left[\int_t^\infty e^{-r(s-t)} D_{is} ds \right] = p_D D_{it} + p_m m_i. \tag{H.56}$$

Substituting Equation (H.56) into Equation (31) yields

$$P_{it} = p_{\gamma_i} + \mathbb{E}_t \left[\int_t^\infty e^{-r(s-t)} D_{is} ds \right] + p_{f_{it}} + \theta \left[q_{it}^\star V_t^A + \lambda_{it} V_t^P \right], \tag{H.57}$$

where $p_{\gamma_i} = -\frac{\gamma}{r^2} \sum_j \omega_i \omega_j \varrho_{ij}$ represents the compensation for earnings risk. Thus,

$$\mathbb{E}_t^* \left[\int_t^\infty e^{-r(s-t)} D_{is} ds \right] = p_{\gamma_i} + \mathbb{E}_t \left[\int_t^\infty e^{-r(s-t)} D_{is} ds \right]. \tag{H.58}$$

Consequently, the equilibrium formulation in Proposition 2 corresponds to the pricing function conjectured in Equation (31), which was verified above. Q.E.D.

TABLE I: **Summary statistics of funds with static equity allocation: alternative classification based on coefficient of variation.** The table reports annual statistics for static funds from the CRSP Mutual Fund Database. Static funds are defined as mutual funds and ETFs with coefficient of variation of the fraction of the portfolio allocated to common stocks $\leq 5\%$ computed over an expanding window of at least eight quarters of history. Wealth flows are annual totals computed following Lou (2012). TNA is aggregate total net assets across all static funds, expressed in trillions of dollars and measured at year end. U.S. Equity Exposure is the aggregate dollar exposure of static funds to U.S. equities, computed as the sum across funds of each fund's TNA multiplied by equity allocation, and measured at year end. Percentage of U.S. Stock Market Held by Static Funds is the ratio of Static Funds' U.S. Equity Exposure to U.S. Stock Market Capitalization measured at year end. Data from CRSP Mutual Fund Summary Files for the period 2004–2024.

Model Counterpart	πdF_t	V_t	θV_t	P_t	Q_t
Year	Wealth Flows ($Bn)	TNA ($T)	U.S. Equity Exposure ($T)	U.S. Stock Market Cap ($T)	% U.S. Stock Market Held by Static Funds
2004	18.51	2.11	1.98	16.46	12.01
2005	8.67	2.28	2.14	17.38	12.32
2006	-18.12	2.52	2.38	19.62	12.13
2007	22.38	2.93	2.78	20.22	13.73
2008	2.05	1.75	1.65	12.14	13.57
2009	-38.59	2.20	2.10	15.83	13.27
2010	-73.66	2.63	2.49	18.52	13.45
2011	-59.13	2.47	2.31	17.90	12.92
2012	-77.98	2.66	2.50	20.39	12.28
2013	93.82	3.45	3.25	26.33	12.35
2014	-5.45	3.70	3.50	29.01	12.08
2015	-79.01	3.75	3.56	27.69	12.84
2016	-34.64	3.92	3.72	30.18	12.31
2017	-52.14	4.02	3.86	35.76	10.79
2018	-46.40	4.28	4.11	32.57	12.62
2019	-169.91	5.24	5.05	41.16	12.27
2020	-251.30	6.02	5.82	49.84	11.67
2021	73.76	6.99	6.77	63.18	10.71
2022	28.81	5.89	5.69	49.72	11.44
2023	-101.40	6.66	6.45	60.70	10.63
2024	102.05	7.50	7.28	74.03	9.83
Mean	-31.32	3.95	3.78	32.32	12.15

TABLE II: **U.S. stock market expected returns and ownership by funds with static equity allocation, quarterly data**. Panel A reports ordinary least squares quarterly estimates of the regression

$$r^e_{t,t+h} = \alpha_h + \beta_h \tilde{y}_t + \gamma_h z_t + \varepsilon_{t+h}.$$

Panel B reports ordinary least squares quarterly estimates of the benchmark regression

$$r^e_{t,t+h} = \alpha_h + \beta_h y_t + \varepsilon_{t+h}.$$

Panel C reports out-of-sample R^2 computed following Welch and Goyal (2008), using a recursive expanding window of 20 in-sample quarters. $r^e_{t,t+h}$ denotes the cumulative log market return in excess of the risk-free rate from quarter t to $t+h$. $y_t = \log(\frac{D_t}{P_t})$ denotes the dividend yield. In the model, the dividend yield admits the decomposition $y_t = \tilde{y}_t - z_t$, where $\tilde{y}_t = \log(\frac{D_t}{P_t - \theta V_t})$ and $z_t = -\log(1 - Q_t)$. t-statistics are computed using Hodrick (1992) standard errors and reported in brackets underneath the coefficients. One-sided p-values are used for $y_t > 0$, $\tilde{y}_t > 0$, and $z_t < 0$, as implied by the literature and the model. One, two, and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively. Quarterly data from CRSP Mutual Fund Summary Files for the period 2004–2024.

	1 quarter	2 quarters	3 quarters	4 quarters	5 quarters	6 quarters
Panel A. Decomposed specification						
$\tilde{y}_t$	0.175**	0.413***	0.592***	0.746***	0.815***	0.985***
	[1.97]	[2.70]	[2.84]	[3.01]	[2.90]	[3.02]
z_t	−2.250**	−5.642***	−7.577**	−9.167**	−8.892*	−9.938*
	[−1.90]	[−2.46]	[−2.17]	[−2.00]	[−1.62]	[−1.49]
$\overline{R}^2$	0.045	0.164	0.229	0.290	0.297	0.367
N	79	78	77	76	75	74
Panel B. Benchmark specification						
y_t	0.086	0.201*	0.323*	0.435**	0.527**	0.675**
	[1.17]	[1.43]	[1.62]	[1.74]	[1.78]	[2.02]
$\overline{R}^2$	0.017	0.060	0.109	0.156	0.198	0.272
N	79	78	77	76	75	74
Panel C. Out-of-sample R^2						
Decomposed	0.046	0.153	0.066	0.101	0.188	0.374
Benchmark	0.022	0.064	0.110	0.162	0.198	0.271
Difference	0.024	0.089	−0.045	−0.060	−0.010	0.104
N	60	59	58	57	56	55

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

Ruggero Jappelli

Internet Appendix A: Flexible Asset Allocation Targets

This appendix considers the robustness of Proposition 1 to a case in which static investors adopt a strategy with flexible asset allocation targets, defined as the convex combination of a fixed benchmark $\bar{\theta}$ and a state-contingent component $\hat{\theta}$. Namely,

$$\theta_t = (1-\tau)\bar{\theta} + \tau\hat{\theta}_t, \qquad \tau \in [0,1]. \tag{IA.A1}$$

The parameter τ governs flexibility over a continuum of cases, with $\tau = 0$ reproducing constant portfolio weights and $\tau = 1$ corresponding to fully state-contingent targets. For simplicity, the state-contingent asset allocation target, $\hat{\theta}$, is specified so as to replicate the optimal policy of dynamic investors. Namely,

$$\hat{\theta}_t = X_t^\star P_t / W_t. \tag{IA.A2}$$

This policy is always feasible, because there are no borrowing or short-selling constraints. Equation (IA.A2) implies that a proportion τ of the wealth of static investors is invested optimally, as is the wealth of the dynamic investors. In this case, it can be shown that the equilibrium valuation of the stock market is given by:

$$P_t = \underbrace{\mathbb{E}_t^*\left[\int_t^\infty e^{-r(s-t)} D_s ds\right]}_{\textit{Fundamentals}} + \underbrace{(1-\tau)\Big[-\gamma\bar{\theta}\pi^2 + \bar{\theta}V_t\Big]}_{\textit{Asset classification effect}}. \tag{IA.A3}$$

Thus, allowing mandates to adjust with states does not eliminate the asset classification effect, which persists whenever targets retain a fixed element, i.e., $\tau < 1$.

Internet Appendix B: Wealth Flows and Earnings News

This appendix considers the robustness of Proposition 1 to a case in which wealth flows and earnings news are correlated. Thus far, wealth flows, dF_t, were assumed to be uncorrelated with earnings news, dB_t, and thus with changes in dividends, dD_t (recall that $D_t = aE_t$ and the earnings payout ratio a is normalized to one). However, wealth invested in funds following static allocation strategies may partly reflect information about earnings, as some agents could use static funds interchangeably with direct exposure to stocks. 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 specification

$$dF_t = \rho dB_t + \sqrt{1-\rho^2}dU_t, \tag{IA.B4}$$

where U_t is a Brownian motion uncorrelated with earnings news. It is assumed that $0 < \rho < 1$, which is economically plausible, considering that some fund shareholders are sophisticated and time their exposure to the fund in response to earnings news, while other fund shareholders are inertial and unresponsive to earnings news. Conjecture the equilibrium stock market valuation

$$P_t = \widehat{p}_\gamma + p_D D_t + p_m m + \theta V_t, \tag{IA.B5}$$

where $\widehat{p}_\gamma$ is a constant to be determined. Static investors' wealth follows

$$dV_t = rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi dF_t. \tag{IA.B6}$$

Substituting Equations (IA.B4) and (IA.B6) into $dP_t = p_D dD_t + \theta dV_t$ yields

$$dP_t = p_D dD_t + \theta[rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi(\rho dB_t + \sqrt{1-\rho^2}dU_t)]. \tag{IA.B7}$$

In light of Equation (1) for dD_t and rearranging terms, the price drift and diffusion coefficients satisfy

$$\mu_t = \frac{p_D m + \theta[rV_t(1-\theta) + Q_t D_t]}{1-\theta Q_t}, \tag{IA.B8}$$

$$\sigma_t = \frac{\sqrt{(p_D\omega + \theta\pi\rho)^2 + \theta^2\pi^2(1-\rho^2)}}{1-\theta Q_t}. \tag{IA.B9}$$

Hence, relative to Proposition 1, the loading on the earnings shock dB_t becomes $p_D\omega + \theta\pi\rho$, while the loading on the orthogonal flow shock dU_t becomes $\theta\pi\sqrt{1-\rho^2}$. To verify the conjecture in Equation (IA.B5), the portfolio FOC of dynamic investors and the market clearing condition must be jointly satisfied. The portfolio FOC is

$$\mu_t - rP_t + D_t = r\gamma(1-Q_t)\frac{E_t[dP_t^2]}{dt} + g'(V_t)\frac{E_t[dP_t dV_t]}{dt}. \tag{IA.B10}$$

Using Equation (IA.B5), the left-hand side of (IA.B10) satisfies

$$\mu_t - rP_t + D_t = -\frac{r\widehat{p}_\gamma}{1-\theta Q_t}. \tag{IA.B11}$$

Moreover,

$$\frac{E_t[dP_t^2]}{dt} = \frac{p_D^2\omega^2 + 2\theta p_D\omega\pi\rho + \theta^2\pi^2}{(1-\theta Q_t)^2}, \tag{IA.B12}$$

and

$$\frac{E_t[dP_t dV_t]}{dt} = \frac{Q_t(p_D^2\omega^2 + \theta p_D\omega\pi\rho) + p_D\omega\pi\rho + \theta\pi^2}{(1-\theta Q_t)^2}. \tag{IA.B13}$$

Substituting these expressions into the portfolio FOC and multiplying both sides by $(1-\theta Q_t)^2$,

$$\begin{aligned} -r\widehat{p}_\gamma(1-\theta Q_t) = {} & r\gamma(1-Q_t)(p_D^2\omega^2 + 2\theta p_D\omega\pi\rho + \theta^2\pi^2) \\ & + g'(V_t)[Q_t(p_D^2\omega^2 + \theta p_D\omega\pi\rho) + p_D\omega\pi\rho + \theta\pi^2]. \end{aligned} \tag{IA.B14}$$

This equality must hold for all states. Matching the constant terms yields

$$-r\widehat{p}_\gamma = r\gamma(p_D^2\omega^2 + 2\theta p_D\omega\pi\rho + \theta^2\pi^2) + g'(V_t)(p_D\omega\pi\rho + \theta\pi^2). \tag{IA.B15}$$

Matching the coefficient multiplying Q_t yields

$$r\theta\widehat{p}_\gamma = -r\gamma(p_D^2\omega^2 + 2\theta p_D\omega\pi\rho + \theta^2\pi^2) + g'(V_t)(p_D^2\omega^2 + \theta p_D\omega\pi\rho). \tag{IA.B16}$$

Adding θ times the Equation (IA.B15) to Equation (IA.B16) yields

$$0 = -r\gamma(1-\theta)(p_D^2\omega^2 + 2\theta p_D\omega\pi\rho + \theta^2\pi^2) + g'(V_t)(p_D^2\omega^2 + 2\theta p_D\omega\pi\rho + \theta^2\pi^2). \tag{IA.B17}$$

Thus,

$$g'(V_t) = (1-\theta)r\gamma. \tag{IA.B18}$$

Substituting this expression into Equation (IA.B15) yields

$$\widehat{p}_\gamma = -\gamma[p_D^2\omega^2 + (1+\theta)p_D\omega\pi\rho + \theta\pi^2]. \tag{IA.B19}$$

The remaining aspects of dynamic investors' optimization program are unchanged relative to the benchmark model. Substituting the optimal policy rules into the HJB verifies the conjecture exactly as in Appendix B. The derivations carry over verbatim, and are thus omitted for brevity. Setting $\rho = 0$ yields $\widehat{p}_\gamma = p_\gamma$, recovering the benchmark equilibrium in Proposition 1. The asset classification effect extends naturally to an environment in which wealth flows and earnings news are correlated. Q.E.D.

Internet Appendix C: Wealth Flows with Drift

This appendix considers the robustness of Proposition 1 to a case in which wealth flows into the static fund have a constant drift term. Suppose that the flow process satisfies

$$dF_t = \upsilon dt + d\widetilde{F}_t, \tag{IA.C1}$$

where $\widetilde{F}_t$ is a Brownian motion adapted to $\{\mathcal{F}_t\}$, and υ is a constant drift term. I show that this environment is equivalent to the benchmark after a change of variables. Substituting Equation (IA.C1) into the static investors' wealth dynamics in Equation (5) yields

$$dV_t = rV_t(1-\theta)dt + Q_t(dP_t + D_t dt) + \pi\upsilon dt + \pi d\widetilde{F}_t. \tag{IA.C2}$$

As the risk-adjusted expected return on stocks must equal the risk-free rate,

$$\mathbb{E}_t^*[dV_t] = rV_t dt + \pi\upsilon dt + \mathbb{E}_t^*[\pi d\widetilde{F}_t]. \tag{IA.C3}$$

The last term is the same flow-risk adjustment as in Proposition 1,

$$\mathbb{E}_t^*[\pi d\widetilde{F}_t] = -\gamma r\pi^2 dt. \tag{IA.C4}$$

Hence,

$$\mathbb{E}_t^*[dV_t] = rV_t dt + \pi\upsilon dt - \gamma r\pi^2 dt. \tag{IA.C5}$$

Define the auxiliary wealth process

$$\widetilde{V}_t = V_t + \frac{\pi\upsilon}{r}. \tag{IA.C6}$$

Given that the term $\frac{\pi\upsilon}{r}$ is constant, $d\widetilde{V}_t = dV_t$, and Equation (IA.C5) implies

$$\mathbb{E}_t^*[d\widetilde{V}_t] = r\widetilde{V}_t dt - \gamma r\pi^2 dt. \tag{IA.C7}$$

Equation (IA.C7) shows that the auxiliary static investors' wealth changes exhibit the same risk-adjusted drift coefficient as static investors' wealth changes in the benchmark economy. Accordingly, conjecture that the equilibrium pricing function is

$$P_t = p_\gamma + p_D D_t + p_m m + \theta\widetilde{V}_t. \tag{IA.C8}$$

The verification in Appendix B carries over verbatim, with $\widetilde{V}_t$ in place of V_t. Expressing the conjecture in Equation (IA.C7) in terms of V_t,

$$P_t = p_\gamma^\upsilon + p_D D_t + p_m m + \theta V_t, \tag{IA.C9}$$

where

$$p_\gamma^\upsilon = p_\gamma + \frac{\theta\pi\upsilon}{r}. \tag{IA.C10}$$

Setting $\upsilon = 0$ recovers the benchmark of Proposition 1. Thus, the asset classification effect extends naturally to an environment in which static investors receive wealth flows with a drift.