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Passive Investing and the Rise of Mega-Firms

Hao Jiang
Michigan State University

Dimitri Vayanos
London School of Economics, CEPR and NBER

Lu Zheng
University of California–Irvine

We study how passive investing affects asset prices. Flows into passive funds disproportionately raise the stock prices of the economy's largest firms, especially those large firms in high demand by noise traders. Because of this effect, the aggregate market can rise even when flows are entirely due to investors switching from active to passive funds. Intuitively, passive flows increase the idiosyncratic risk of large firms in high demand, which discourages investors from correcting the flows' effects on prices. Consistent with our theory, prices and idiosyncratic volatilities of the largest S&P500 firms rise the most following flows into that index. (*JEL* G12, G23, E44)

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One of the most important capital-market developments of the past 30 years has been the growth of passive investing. Passive funds track market indices and charge lower fees than active funds. In 1993, passive funds invested in

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U.S. stocks managed $23 billion of assets and accounted for 0.44% of the U.S. stock market. By 2021, passive assets had risen to $8.4 trillion and accounted for 16% of the market.[1] The growth of passive investing has been estimated to be more than twice as high when accounting for the increasing tendency by actively managed mutual funds and other institutional investors to stay close to their benchmark indices.[2]

The growth of passive investing has stimulated academic and policy interest in how it affects asset prices and the real economy. One effect that has been emphasized, drawing from the literature on rational expectations equilibria (REE) with asymmetric information (Grossman 1976; Grossman and Stiglitz 1980), is that with fewer active funds, individual stocks become less liquid and their prices less informative. Another effect, drawing from the literature on index additions (Harris and Gurel 1986; Shleifer 1986), is that the prices of the stocks included in the indices tracked by passive funds rise, while the prices of non-index stocks do not.

In this paper we show that the growth of passive investing disproportionately raises the stock prices of the economy's largest firms, especially those large firms in high demand by noise traders. Passive investing thus reduces primarily the financing costs of the largest firms and makes the size distribution of firms more skewed. These effects are generated by a different mechanism than in the REE and index-addition literatures because information in our model is symmetric and the effects arise even when indices include all firms. We also show that the effects on the largest firms can be sufficiently strong to cause the aggregate market to rise even when the growth of passive funds comes entirely from investors switching from active funds (and not from new investors entering into stocks). Passive investing thus biases the stock market toward overvaluation. Consistent with our theory, we find that the prices of the largest firms in the S&P500 index rise the most following flows into that index.

The intuition for our results can be conveyed through a stylized example. Consider a large firm that is in such high demand by noise traders (e.g., retail investors) that active funds short-sell it in equilibrium.[3] A switch by some investors from active to passive funds generates additional demand for the firm because passive funds hold the firm with its weight in the market index

[1] The data come from the 2022 Investment Company Institute (ICI) Factbook (Figure 2.9 and Tables 11 and 42) and from https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?locations=US. We identify passive funds with index mutual funds and exchange-traded funds (ETFs), and identify more generally passive investing with indexing throughout this paper.

[2] A measure of how far active funds stray from their benchmark indices is active share, defined in Cremers and Petajisto (2009). Petajisto (2013) finds that active share has been declining over time. Chinco and Sammon (2024) estimate that passive investing under its broader definition comprised 33.3% of the U.S. stock market in 2021.

[3] Active funds in this example can be more naturally interpreted as hedge funds rather than as actively managed mutual funds because the former can short-sell but the latter typically cannot. The interpretation can be broadened, however, to actively managed mutual funds that must keep their deviations from market indexes within tracking-error bounds. Indeed, because of the bounds, the mutual funds face a risk from underweighting large firms, and that risk increases when firms' stock prices rise.

while active funds hold it with negative weight. Active funds can accommodate the additional demand by scaling up their short position. This renders them, however, more exposed to the firm's idiosyncratic risk, which is non-negligible because the firm is large. The firm's stock price must then rise to induce active funds to take on the additional risk. Crucially, because the stock price rises, the stock's idiosyncratic price movements become larger in absolute terms. This gives rise to an amplification loop: the short position of active funds becomes even riskier, causing the stock's price to rise even further, and the stock's idiosyncratic price movements to become even larger.

The amplification loop explains why passive flows have their largest effects on large firms in high demand by noise traders. It also explains why the effects of passive flows on these firms can be sufficiently strong so that a switch from active to passive causes the aggregate market to rise even though the stock prices of other firms might drop. It further explains why passive flows raise the idiosyncratic volatility of large firms more than of smaller firms, a result that we confirm empirically.

In our model, presented in Section 1, agents can invest in a constant riskless rate and in multiple stocks, over an infinite horizon. Each stock's dividend flow per share is the sum of a constant component and of a systematic and an idiosyncratic component that follow independent square-root processes. Some agents, the experts, can invest in all assets without constraints. They can be interpreted as investors holding actively managed mutual funds and exchange-traded funds (ETFs) as well as hedge funds. Other agents, the non-experts, can only invest in the riskless asset and in a capitalization-weighted index. They can be interpreted as investors holding passive funds. Experts and non-experts maximize a mean-variance objective over instantaneous changes in wealth. Noise traders can also be present, and they hold a number of shares of each stock that is constant over time.

In the equilibrium of the model, derived in Section 2, the price of a stock is the sum of the present values of the constant, systematic, and idiosyncratic dividends. The discount rate for idiosyncratic dividends increases in the stock's supply held by experts and is approximately equal to the riskless rate for all but the largest stocks. The discount rate for systematic dividends increases in the aggregate supply of all stocks held by experts.

Section 3 shows analytically how stock prices respond to an increase in the measure of non-experts. When the measure of experts is held constant in this exercise, passive flows are due to entry by new investors into the stock market. When instead the measure of experts and non-experts is held constant, passive flows are due to a switch from active to passive. In a capital asset pricing model (CAPM) world where the index includes all stocks and noise traders are absent, a switch from active to passive leaves stock prices unchanged because experts and non-experts hold the same portfolio. When instead passive flows are not entirely due to a switch from active, their effect is an increasing function of CAPM beta for all but the largest stocks and exceeds that function for the largest stocks. Intuitively, passive flows lower the market risk premium, and this lowers the discount rates for systematic and idiosyncratic dividends. The effect on the largest stocks is disproportionately large because changes to the idiosyncratic discount rate (i) are approximately equal to zero for all but the largest stocks and (ii) have a larger effect on the present value of idiosyncratic dividends than equal changes to the systematic discount rate have on the present value of systematic dividends due to the idiosyncratic rate being lower than the systematic rate.

Section 4 calibrates the model using data on moments of stock returns and the size distribution of firms. The calibration assumes approximately 1,700 firms sorted into five size groups based on the aggregate dividends that firms pay to their shareholders. The assumed size distribution of firms conforms to a power law with exponent one, consistent with the empirical evidence (Axtell 2001). We consider the case where the relative size of the systematic and idiosycratic components of dividends is the same for all stocks, and the case where the systematic component decreases with firm size in a way that generates the empirical negative relationship between size and CAPM beta (Fama and French 1992). Consistent with the analytical results of Section 3, passive flows have disproportionately large effects on the firms in the largest size group. Furthermore, when noise traders are present, the effects of passive flows are strongest for those firms in the largest size group that are in high demand by noise traders.

Section 5 presents tests of our theory and relates our results to empirical findings in the literature. We take the index to be the S&P500 and flows to be into index mutual funds and index ETFs tracking it. Our flow data are quarterly from 1996 to 2020. During quarters when index funds receive high inflows, the largest stocks in the index outperform the index. Following the same quarters, the idiosyncratic return volatility of the largest stocks increases more than of smaller stocks. In an additional test, we find that the largest stocks in the S&P600 index, which is made up of small stocks, do not outperform that index following passive flows into it. This aligns with our theoretical results: passive flows into an index disproportionately raise the stock prices of the index's largest firms only when these firms are also the largest in the economy.

The effects of passive investing have been analyzed mainly within the framework proposed by Grossman and Stiglitz (1980, hereafter GS), in which informed and uninformed investors trade with noise traders. Informed and uninformed investors in GS can be interpreted as active and passive fund managers, respectively. A switch from active to passive lowers informational efficiency and can exacerbate the mispricing induced by noise traders.[4] The interpretation of GS investors as fund managers is developed in

[4] Pastor and Stambaugh (2012) and Stambaugh (2014) explain an increase in market efficiency, as reflected in a decline in active funds' expected returns, by the increase in the assets that active funds manage and by the decline in noise trading, respectively.

Garleanu and Pedersen (2018), in which investors search for informed managers, and the efficiency of the search market for managers affects the efficiency of the asset market. In Subrahmanyam (1991), the introduction of a market index facilitates passive investing and lowers liquidity for the assets that comprise the index. A switch from active to passive exacerbates noise-trader mispricing in our model as well. Our main results, however, concern how the effects of passive flows depend on stock size, and they hold even in the absence of noise traders.[5]

A different strand of literature studies how constraints or incentives of fund managers to not deviate from their benchmark indices affect asset prices. Brennan (1993), Kapur and Timmermann (2005), Cuoco and Kaniel (2011), and Basak and Pavlova (2013) show that compensating managers based on their performance relative to indices induces them to buy index assets, causing their prices to rise. Davies (2024) shows that passive flows have their strongest positive effects on the prices of stocks with high CAPM beta or in high demand by noise traders. Our model nests these results while also yielding the effects for the largest stocks. Chabakauri and Rytchkov (2021) show that passive flows cause market volatility to decrease when they are due to a switch from active to passive, and to increase when they are due to entry by new investors into the stock market. Our model is closest to that of Buffa, Vayanos, and Woolley (2022, hereafter BVW), who examine how constraints on managers' deviations from indices affect asset prices. We depart from BVW by introducing systematic risk and a size distribution of firms.

Our theory has implications for recent macroeconomic trends such as the rise in industry concentration and the decline in corporate investment. Autor et al. (2020) show that the rise of superstar firms can account for the rise in concentration (Grullon, Larkin, and Michaely 2019) and the decline in the labor share (Elsby, Hobijn, and Sahin 2013; Karabarbounis and Neiman 2014). Our theory suggests that the growth of passive investing can be one factor behind the rise of superstar firms, through the steeper decline of their financing costs. Alexander and Eberly (2018) and Crouzet and Eberly (2023) attribute

[5] Some papers show that the rise in passive investing can raise informational efficiency for individual stocks. In Bond and Garcia (2022), a decrease in the costs of index investing induces uninformed traders to switch to trading the index from trading individual stocks, and this lowers informational efficiency for the index but raises it for individual stocks. In Buss and Sundaresan (2023), passive investing can increase market efficiency when corporate investment responds to stock prices. On the empirical side, Ben-David, Franzoni, and Moussawi (2018) and Da and Shive (2018) find that the introduction of ETFs lowers informational efficiency for the underlying stocks because non-fundamental demand shocks spill over across stocks. Brogaard, Ringgenberg, and Sovich (2018) likewise find that the introduction of commodity indices results in worse production decisions by commodity firms. Ben-David et al. (2022) find additionally that ETFs are often introduced to cater to investor sentiment. Bhojraj, Mohanram, and Zhang (2020) find instead that the introduction of sector ETFs renders stock prices more responsive to sector-level fundamental information. Glosten, Nallareddy, and Zou (2020) likewise find that ETFs render stock prices more responsive to economy-wide information, in the case of small stocks or stocks with low analyst coverage. Antoniou et al. (2022) find that ETFs cause firms' investment decisions to become more tightly linked to stock prices. Coles, Heath, and Ringgenberg (2022) and Koijen, Richmond, and Yogo (2024) find that the growth of passive investing does not have a significant impact on market efficiency. Haddad, Huebner, and Loualiche (2025) find that the growth of passive investing is associated with less price-elastic asset demand curves.

the decline in corporate investment (Hall 2014) to intangible capital, while Gutiérrez and Philippon (2017) and Covarrubias, Gutiérrez, and Philippon (2019) show that the rise in concentration and changes in corporate governance are additional causes. Our theory suggests that the growth of passive investing may also have played a role because large overvalued firms experience the steepest decline in their financing costs but may not have the best investment projects.[6]

1. Model

Time t is continuous and goes from zero to infinity. The riskless rate is exogenous and equal to $r>0$. There are N firms indexed by $n=1,..,N$. The stock of firm n, also referred to as stock n, pays dividend flow D_{nt} per share and is in supply of $\eta_n>0$ shares. The dividend flow of stock n is

$$D_{nt}=\bar{D}_n+b_n D_t^s+D_{nt}^i, \tag{1.1}$$

the sum of a constant component $\bar{D}_n \geq 0$, a systematic component $b_n D_t^s$, and an idiosyncratic component D_{nt}^i. The systematic component is the product of a systematic factor D_t^s times a factor loading $b_n \geq 0$. The systematic factor follows the square-root process

$$dD_t^s=\kappa^s\left(\bar{D}^s-D_t^s\right)dt+\sigma^s\sqrt{D_t^s}dB_t^s, \tag{1.2}$$

where $(\kappa^s,\bar{D}^s,\sigma^s)$ are positive constants and B_t^s is a Brownian motion. The idiosyncratic component follows the square-root process

$$dD_{nt}^i=\kappa_n^i\left(\bar{D}_n^i-D_{nt}^i\right)dt+\sigma_n^i\sqrt{D_{nt}^i}dB_{nt}^i, \tag{1.3}$$

where $\{\kappa_n^i,\bar{D}_n^i,\sigma_n^i\}_{n=1,..,N}$ are positive constants and $\{B_{nt}^i\}_{n=1,..,N}$ are Brownian motions that are mutually independent and independent of B_t^s. By possibly redefining factor loadings and the parameters of the square-root process in Equation (1.2), we set the long-run mean $\bar{D}^s$ of the systematic factor to one. By possibly redefining the supply η_n, the factor loading b_n and the parameters of the square-root process in Equation (1.3), we set the long-run mean $\bar{D}_n+b_n+\bar{D}_n^i$ of the dividend flow of stock n to one for all n.

Our specification in Equations (1.1)–(1.3) for dividends differs from typical specifications in the asset-pricing literature in two main respects. First, dividends are typically assumed to be nonstationary, while our specification yields stationarity because the systematic and idiosyncratic components of dividends mean-revert. Second, the volatility of dividends per share is typically assumed to be proportional to their level. That is the case, for example,

[6] Gutiérrez and Philippon (2017) find that firms with a large share of ownership by passive funds invest less. They emphasize governance-based explanations rather than valuation-based ones.

when dividends follow a geometric Brownian motion. Under our specification instead, the volatility of the systematic and idiosyncratic components of dividends is proportional to the square root of their level.

Our model yields a nonstationary specification in the limit where the mean-reversion parameters $(\kappa^s, \{\kappa_n^i\}_{n=1,..,N})$ converge to zero. The analytical results shown in Section 3 carry through to that limit. Moreover, the calibration results shown in Section 4 remain similar across different values of $(\kappa^s, \{\kappa_n^i\}_{n=1,..,N})$. Thus, while stationarity yields a stochastic steady state in which we can compute unconditional moments of returns, it does not seem important for our results.

We assume that the volatility of dividends per share is proportional to the square root of their level rather than to the level itself for tractability. The square-root specification preserves two important properties of typical specifications. First, dividends always remain positive. This is because when they converge to zero, their volatility converges to zero while their mean reversion pulls them toward their positive long-run mean. Second, the volatility of dividends per share increases in their level. This property is key for our results, as we explain in Sections 2 and 3. In Internet Appendix C we show that the volatility of dividends per share of individual firms in the data increases in the level of dividends per share. Moreover, the increase appears to be concave rather than linear, consistent with a square-root specification. In Internet Appendix D we use a three-period model to show that when the volatility of dividends per share is proportional to their level or to the square-root of their level, results are similar. We confine ourselves to three periods in Internet Appendix D to ensure that the analysis of the level specification remains tractable, and we eliminate the mean-reversion so that the level specification becomes a geometric random walk.

Denoting by S_{nt} the price of stock n, the stock's return per share in excess of the riskless rate is

$$dR_{nt}^{sh} \equiv D_{nt}dt + dS_{nt} - rS_{nt}dt, \tag{1.4}$$

and the stock's return per dollar in excess of the riskless rate is

$$dR_{nt} \equiv \frac{dR_{nt}^{sh}}{S_{nt}} = \frac{D_{nt}dt + dS_{nt}}{S_{nt}} - rdt. \tag{1.5}$$

We refer to dR_t^{sh} as share excess return. We refer to dR_t as excess return, omitting that it is per dollar. All moments that we compute in our calibration in Section 4 concern dR_t.

Agents are competitive and form overlapping generations living over infinitesimal time intervals. We assume infinitesimal lifespans for tractability because they yield simple mean-variance preferences, as we show later. Each generation of agents includes experts and non-experts. Experts can invest in the riskless asset and in the stocks without constraints. These agents can be interpreted as investors holding actively managed mutual funds and ETFs as well as hedge funds. Non-experts can invest in the riskless asset and in a stock portfolio that tracks an index. These agents can be interpreted as investors holding passive funds.[7]

In addition to experts and non-experts, noise traders can be present. These agents generate an exogenous demand for each stock, which is smaller than the supply coming from the issuing firm. For tractability, we take the demand by noise traders to be constant over time when expressed in number of shares. A constant demand can capture slowly mean-reverting market sentiment. When noise traders are absent, or when their demand is proportional to the firm-issued supply in the cross-section of stocks, experts and non-experts hold the same portfolio of stocks in equilibrium.

The index includes all stocks or a subset of them. It is capitalization-weighted over the stocks that it includes—that is, it weights them proportionately to their market capitalization. We refer to the included and the non-included stocks as index and non-index stocks, respectively. We denote by $\mathcal{I}$ the subset of index stocks, by $\mathcal{I}^c$ its complement, and by η'_n the number of shares of stock n included in the index. Since the index is capitalization-weighted over the stocks that it includes, η'_n for $n \in \mathcal{I}$ is proportional to the number of shares η_n issued by firm n. By possibly rescaling the index, we set $\eta'_n = \eta_n$ for $n \in \mathcal{I}$. For $n \in \mathcal{I}^c$, $\eta'_n = 0$.

We denote by W_{1t} and W_{2t} the wealth of an expert and a non-expert, respectively, by z_{1nt} and z_{2nt} the number of shares of stock n that these agents hold, and by μ_1 and μ_2 these agents' measure. A non-expert thus holds $z_{2nt} = \lambda \eta'_n$ shares of stock n, where λ is a proportionality coefficient that the agent chooses optimally. We assume for tractability that non-experts choose λ once and for all at time zero and under the unconditional distribution of dividends. We denote by $u_n < \eta_n$ the number of shares of stock n held by noise traders.

Experts and non-experts born at time t are endowed with wealth W. Their budget constraint is

$$dW_{it} = \left(W - \sum_{n=1}^{N} z_{int} S_{nt} \right) r dt + \sum_{n=1}^{N} z_{int} (D_{nt} dt + dS_{nt}) = W r dt + \sum_{n=1}^{N} z_{int} dR_{nt}^{sh}, \tag{1.6}$$

where dW_{it} is the infinitesimal change in wealth over their life, $i = 1$ for experts, and $i = 2$ for non-experts. They have mean-variance preferences over dW_{it}. Given infinitesimal lifespans, mean-variance preferences can be derived from any VNM utility u, using the second-order Taylor expansion

$$u(W + dW_{it}) = u(W) + u'(W) dW_{it} + \frac{1}{2} u''(W) dW_{it}^2 + o(dW_{it}^2). \tag{1.7}$$

[7] Investors' choice to invest in active or passive funds can result from trading off the superior returns on active funds with their higher fees, in the spirit of Grossman and Stiglitz (1980).

Experts maximize the conditional expectation of Equation (1.7). This is equivalent to maximizing

$$\mathbb{E}_t(dW_{1t})-\frac{\rho}{2}\mathbb{V}\mathrm{ar}_t(dW_{1t}) \tag{1.8}$$

with $\rho=-\frac{u''(W)}{u'(W)}$, because infinitesimal dW_{1t} implies that $\mathbb{E}_t(dW_{1t}^2)$ is equal to $\mathbb{V}\mathrm{ar}_t(dW_{1t})$ plus smaller-order terms. Non-experts maximize the unconditional expectation of Equation (1.7). This is equivalent to maximizing

$$\mathbb{E}(dW_{2t})-\frac{\rho}{2}\mathbb{V}\mathrm{ar}(dW_{2t}), \tag{1.9}$$

because infinitesimal dW_{2t} implies that $\mathbb{E}(dW_{2t}^2)$ is equal to $\mathbb{V}\mathrm{ar}(dW_{2t})$ plus smaller-order terms.

2. Equilibrium

We look for an equilibrium where the price S_{nt} of stock n is

$$S_{nt}=\bar{S}_n+b_nS^s(D_t^s)+S_n^i(D_{nt}^i), \tag{2.1}$$

the sum of the present value $\bar{S}_n$ of dividends from the constant component, the present value $b_nS^s(D_t^s)$ of dividends from the systematic component, and the present value $S_n^i(D_{nt}^i)$ of dividends from the idiosyncratic component. Assuming that the functions $(S^s(D_t^s), S_n^i(D_{nt}^i))$ are twice continuously differentiable, we can write the share excess return dR_{nt}^{sh} of stock n as

$$\begin{aligned} dR_{nt}^{sh} &= (\bar{D}_n+b_nD_t^s+D_{nt}^i)dt+(b_ndS^s(D_t^s)+dS_n^i(D_{nt}^i)) \\ &\quad -r(\bar{S}_n+b_nS^s(D_t^s)+S_n^i(D_{nt}^i))dt \\ &= \mu_{nt}dt+b_n\sigma^s\sqrt{D_t^s}(S^s)'(D_t^s)dB_t^s+\sigma_n^i\sqrt{D_{nt}^i}(S_n^i)'(D_{nt}^i)dB_{nt}^i, \end{aligned} \tag{2.2}$$

where

$$\begin{aligned} \mu_{nt} &\equiv \frac{\mathbb{E}_t(dR_{nt}^{sh})}{dt}=\bar{D}_n-r\bar{S}_n \\ &\quad +b_n\left[D_t^s+\kappa^s(1-D_t^s)(S^s)'(D_t^s)+\frac{1}{2}(\sigma^s)^2D_t^s(S^s)''(D_t^s)-rS^s(D_t^s)\right] \\ &\quad +D_{nt}^i+\kappa_n^i(\bar{D}_n^i-D_{nt}^i)(S_n^i)'(D_{nt}^i)+\frac{1}{2}(\sigma_n^i)^2D_{nt}^i(S_n^i)''(D_{nt}^i)-rS_n^i(D_{nt}^i) \end{aligned} \tag{2.3}$$

is the instantaneous expected share excess return on stock n, and the second step in Equation (2.2) follows from Equations (1.2), (1.3), and Ito's lemma.

Using Equations (1.6) and (2.2), we can write the objective (1.8) of experts as

$$\sum_{n=1}^{N} z_{1nt}\mu_{nt} - \frac{\rho}{2}\left[\left(\sum_{n=1}^{N} z_{1nt} b_n\right)^2 (\sigma^s)^2 D_t^s [(S^s)'(D_t^s)]^2 + \sum_{n=1}^{N} z_{1nt}^2 (\sigma_n^i)^2 D_{nt}^i [(S_n^i)'(D_{nt}^i)]^2\right]. \tag{2.4}$$

Using Equations (1.6), (2.2), and $z_{2nt} = \lambda\eta_n'$, we can likewise write the objective (1.9) of non-experts as

$$\sum_{n=1}^{N} \lambda\eta_n'\mu_n - \frac{\rho}{2}\lambda^2\left[\left(\sum_{n=1}^{N} \eta_n' b_n\right)^2 (\sigma^s)^2 \mathbb{E}\left[D_t^s [(S^s)'(D_t^s)]^2\right] + \sum_{n=1}^{N} \left(\eta_n'\right)^2 (\sigma_n^i)^2 \mathbb{E}\left[D_{nt}^i [(S_n^i)'(D_{nt}^i)]^2\right]\right], \tag{2.5}$$

where $\mu_n \equiv \frac{\mathbb{E}(dR_{nt}^{sh})}{dt} = \mathbb{E}(\mu_{nt})$. Experts maximize Equation (2.4) over positions $\{z_{1nt}\}_{n=1,..,N}$. Non-experts maximize Equation (2.5) over λ. Taking the first-order condition in Equation (2.4) and substituting $\{z_{1nt}\}_{n=1,..,N}$ from the market-clearing equation

$$\mu_1 z_{1nt} + \mu_2 \lambda \eta_n' + u_n = \eta_n, \tag{2.6}$$

which requires that the demand of experts, non-experts, and noise traders equals the supply coming from the issuing firm, we find

$$\mu_{nt} = \rho\left[b_n\left(\sum_{m=1}^{N} \frac{\eta_m - \mu_2\lambda\eta_m' - u_m}{\mu_1} b_m\right)(\sigma^s)^2 D_t^s [(S^s)'(D_t^s)]^2 + \frac{\eta_n - \mu_2\lambda\eta_n' - u_n}{\mu_1}(\sigma_n^i)^2 D_{nt}^i [(S_n^i)'(D_{nt}^i)]^2\right]. \tag{2.7}$$

We look for functions $(S^s(D_t^s), S_n^i(D_{nt}^i))$ that are affine in their arguments,

$$S^s(D_t^s) = a_0^s + a_1^s D_t^s, \tag{2.8}$$

$$S_n^i(D_{nt}^i) = a_{n0}^i + a_{n1}^i D_{nt}^i, \tag{2.9}$$

for positive constants $(a_0^s, a_1^s, \{a_{n0}^i, a_{n1}^i\}_{n=1,..,N})$. Substituting Equations (2.3), (2.8), and (2.9) into (2.7), we can write Equation (2.7) as

$$\begin{aligned}\bar{D}_n - r\bar{S}_n + b_n\left[D_t^s + \kappa^s a_1^s(1-D_t^s) - r(a_0^s + a_1^s D_t^s)\right] \\ + D_{nt}^i + \kappa_n^i a_{n1}^i(\bar{D}_n^i - D_{nt}^i) - r(a_{n0}^i + a_{n1}^i D_{nt}^i) \\ = \rho\left[b_n\left(\sum_{m=1}^N \frac{\eta_m - \mu_2\lambda\eta_m' - u_m}{\mu_1} b_m\right)(\sigma^s a_1^s)^2 D_t^s \right. \\ \left. + \frac{\eta_n - \mu_2\lambda\eta_n' - u_n}{\mu_1}(\sigma_n^i a_{n1}^i)^2 D_{nt}^i\right]. \qquad (2.10)\end{aligned}$$

Identifying terms in D_t^s yields a quadratic equation that determines a_1^s. Identifying terms in D_{nt}^i yields a quadratic equation that determines a_{n1}^i. Identifying the remaining terms yields $\bar{S}_n + b_n a_0^s + a_{n0}^i$. Substituting $(a_1^s, \{a_{n1}^i\}_{n=1,..,N})$ into the first-order condition of non-experts yields an equation for λ, whose solution completes our characterization of the equilibrium. Proposition 2.1 characterizes the equilibrium. The proposition's proof is in Internet Appendix A, where all proofs are gathered.

Proposition 2.1. In equilibrium, the price of stock n is

$$S_{nt} = \frac{\bar{D}_n}{r} + b_n a_1^s\left(\frac{\kappa^s}{r} + D_t^s\right) + a_{n1}^i\left(\frac{\kappa_n^i}{r}\bar{D}_n^i + D_{nt}^i\right), \qquad (2.11)$$

where

$$a_1^s = \frac{2}{r + \kappa^s + \sqrt{(r+\kappa^s)^2 + 4\rho\left(\sum_{m=1}^N \frac{\eta_m - \mu_2\lambda\eta_m' - u_m}{\mu_1} b_m\right)(\sigma^s)^2}}, \qquad (2.12)$$

$$a_{n1}^i = \frac{2}{r + \kappa_n^i + \sqrt{(r+\kappa_n^i)^2 + 4\rho\frac{\eta_n - \mu_2\lambda\eta_n' - u_n}{\mu_1}(\sigma_n^i)^2}}, \qquad (2.13)$$

and $\lambda > 0$ solves

$$\begin{aligned}\left(\sum_{m=1}^N \eta_m' b_m\right)\left(\sum_{m=1}^N (\eta_m - u_m) b_m\right)(\sigma^s a_1^s)^2 + \sum_{m=1}^N \eta_m'(\eta_m - u_m)(\sigma_m^i a_{m1}^i)^2 \bar{D}_m^i \\ = (\mu_1 + \mu_2)\lambda\left[\left(\sum_{m=1}^N \eta_m' b_m\right)^2 (\sigma^s a_1^s)^2 + \sum_{m=1}^N \left(\eta_m'\right)^2 (\sigma_m^i a_{m1}^i)^2 \bar{D}_m^i\right]. \qquad (2.14)\end{aligned}$$

The price depends on $(\mu_1, \mu_2, \sigma^s, \{b_m, \sigma_m^i, \eta_m, \eta_m', u_m\}_{m=1,..,M})$ only through $\left(\sum_{m=1}^N \frac{\eta_m - \mu_2\lambda\eta_m' - u_m}{\mu_1} b_m\right)(\sigma^s)^2$ and $\frac{\eta_n - \mu_2\lambda\eta_n' - u_n}{\mu_1}(\sigma_n^i)^2$, and is decreasing and convex in the latter two variables.

The present value $\bar{S}_n$ of the dividends of stock n that come from the constant component is $\frac{\bar{D}_n}{r}$. This is because constant dividends are discounted at the riskless rate r. The present value $b_n S^s(D^s_t)$ of dividends coming from the systematic component is $b_n a^s_1\left(\frac{\kappa^s}{r}+D^s_t\right)$, and the present value of dividends coming from the idiosyncratic component is $a^i_{n1}\left(\frac{\kappa^i_n \bar{D}^i_n}{r}+D^i_{nt}\right)$. The coefficients a^s_1 and a^i_{n1} are inversely proportional to the discount rates. Indeed, when D^s_t is equal to its long-run mean of one and hence all future expected systematic dividends are equal to b_n, the stream of these dividends is multiplied by $a^s_1\left(\frac{\kappa^s}{r}+1\right)$ and is thus discounted at the rate $\frac{r}{a^s_1(\kappa^s+r)}$. Likewise, when D^i_{nt} is equal to its long-run mean of $\bar{D}^i_n$, the stream of expected idiosyncratic dividends $\bar{D}^i_n$ is discounted at the rate $\frac{r}{a^i_{n1}(\kappa^i+r)}$.

Supply affects the discount rate for systematic dividends through $\left(\sum_{m=1}^N \frac{\eta_m-\mu_2\lambda\eta'_m-u_m}{\mu_1} b_m\right)(\sigma^s)^2$. This is a risk-adjusted measure of the aggregate supply of stocks that each expert holds in equilibrium, and we refer to it as systematic supply. Supply affects the discount rate for idiosyncratic dividends through $\frac{\eta_n-\mu_2\lambda\eta'_n-u_n}{\mu_1}(\sigma^i_n)^2$. This is a risk-adjusted measure of the supply of stock n held by each expert, and we refer to it as idiosyncratic supply. We calculate systematic and idiosyncratic supply as follows. The supply of stock n held by all experts combined is equal to the supply η_n coming from the issuing firm, minus the demand $\mu_2\lambda\eta'_n$ and u_n coming from non-experts and noise traders, respectively. We express it in per-expert terms by dividing by the measure μ_1 of experts. In the case of systematic supply, we risk-adjust by multiplying by the factor loading b_n of stock n and by the square of the diffusion parameter σ^s of the systematic factor, and we aggregate across all stocks. In the case of idiosyncratic supply, we multiply by the square of the diffusion parameter σ^i_n of the idiosyncratic component of the dividends of stock n.

A reduction in systematic or idiosyncratic supply lowers the discount rate of the corresponding component of dividends. The present value of dividends goes up and its movements become larger in absolute terms. Supply generates a positive relationship between price level and price volatility because discounting for risk works multiplicatively. When supply drops, a^s_1 and a^i_{n1} rise, and so do price level and price volatility. Discounting is multiplicative in our model because the volatility of dividends per share is assumed to increase in their level. By contrast, in constant absolute risk aversion (CARA)-normal models, where the volatility of dividends per share is constant, discounting for risk works additively, by discounting expected dividends at the riskless rate and subtracting a term. A reduction in supply in those models raises the price level but does not affect price volatility. A CARA-normal version of our model would generate none of our main results for that reason.[8] Our assumption that the volatility of dividends per share increases in their level is thus key.

3. Passive Flows and Stock Prices: Analytical Results

Passive flows in our model correspond to an increase in the measure μ_2 of non-experts. These flows can arise because of entry by new investors into the stock market, in which case the measure μ_1 of experts is not changing, or because of a switch by investors from active to passive, in which case μ_1 decreases. We nest the two cases by assuming that when μ_2 increases, μ_1 decreases by an amount equal to a fraction $\phi \in [0,1]$ of the increase in μ_2.

Proposition 3.1. Suppose that μ_2 increases and μ_1 decreases by an amount equal to a fraction $\phi \in [0,1]$ of the increase in μ_2. The percentage change in the price of stock n is

$$\frac{1}{S_{nt}}\frac{dS_{nt}}{d\mu_2} = \frac{\rho}{\mu_1 S_{nt}}\left[b_n \left(\sum_{m=1}^{N} \Delta_m b_m\right)(\sigma^s a_1^s)^2 \left(\frac{\kappa^s}{r} + D_t^s\right) F^s + \Delta_n (\sigma_n^i a_{n1}^i)^2 \left(\frac{\kappa_n^i}{r}\bar{D}_n^i + D_{nt}^i\right) F_n^i \right], \tag{3.1}$$

where

$$\Delta_n \equiv -\mu_1 \frac{d}{d\mu_2}\left(\frac{\eta_n - \mu_2\lambda\eta_n' - u_n}{\mu_1}\right) = \frac{d(\mu_2\lambda)}{d\mu_2}\eta_n' + \phi\frac{\mu_2\lambda\eta_n' + u_n - \eta_n}{\mu_1}, \tag{3.2}$$

$$F^s \equiv \frac{1}{\sqrt{(r+\kappa^s)^2 + 4\rho\left(\sum_{m=1}^{N}\frac{\eta_m - \mu_2\lambda\eta_m' - u_m}{\mu_1} b_m\right)(\sigma^s)^2}}, \tag{3.3}$$

$$F_n^i \equiv \frac{1}{\sqrt{(r+\kappa_n^i)^2 + 4\rho\frac{\eta_n - \mu_2\lambda\eta_n' - u_n}{\mu_1}(\sigma_n^i)^2}}. \tag{3.4}$$

To derive the implications of Proposition 3.1, we begin with a baseline case that corresponds to the CAPM. We assume that the index includes all stocks and is thus the market portfolio—that is, $\mathcal{I} = \{1,..,N\}$. We also assume that noise traders hold the same fraction of shares of each stock, i.e., $\#\{\frac{u_m}{\eta_m} : m \in \{1,..,N\}\} = 1$, and denote that fraction by $\hat{u} \in [0,1)$. The latter assumption

[8] The effect of passive flows in such a model would depend only on CAPM beta, without any effect of size. Moreover, a switch by investors from active to passive would leave the value of the index unchanged. Proofs of these results in a two-period model are available upon request.

includes as a special case the absence of noise traders—that is, $u_n = 0$ for all n. Since non-experts and noise traders hold the market portfolio, experts also hold the market portfolio and stocks are priced according to the CAPM.

Simple CAPM logic suggests that the effect of passive flows on a stock's price in the baseline case should increase in the stock's CAPM beta and should not depend on the stock's size. To present that logic and why it fails in our model, we begin with a simple example that is loosely connected to our model but has the advantage of illustrating the generality of the mechanism. We next show that the same mechanism operates within our model.

Consider a stock n that pays dividend flow D_{nt} per share, and suppose that the stock's expected dividend $\bar{D}_n$, the stock's CAPM beta β_n, and the market risk premium (MRP) are constant. Under the CAPM, the stock's price is $S_n = \frac{\bar{D}_n}{r+\beta_n \mathrm{MRP}}$. Since passive flows generate demand for the market portfolio, they lower MRP. The percentage price change that they generate is thus proportional to

$$\frac{1}{S_n}\frac{\partial S_n}{\partial(-\mathrm{MRP})} = \frac{\bar{D}_n \beta_n}{S_n (r+\beta_n \mathrm{MRP})^2} = \frac{\beta_n}{r+\beta_n \mathrm{MRP}}$$

in the cross-section. It increases in β_n and it does not depend on the size of stock n. This is the simple CAPM logic.

To explain why this logic fails in our model, we next modify the example to account for different components of dividends. Suppose that the dividend flow D_{nt} of stock n is the sum of a constant component $\bar{D}_n$, a systematic component $b_n D^s_t$, and an idiosyncratic component D^i_{nt}. Suppose that the expected dividend $\bar{D}^s$ from the systematic factor D^s_t and the factor's CAPM beta β^s are constants, and normalize $\bar{D}^s$ to one. Suppose also that the stock's expected idiosyncratic dividend $\bar{D}^i_n$ and the CAPM beta β^i_n of idiosyncratic dividends are constants, and $\beta^s > \beta^i_n \geq 0$. Under the CAPM, the stock's price is $S_n = \frac{b_n}{r+\beta^s \mathrm{MRP}} + \frac{\bar{D}^i_n}{r+\beta^i_n \mathrm{MRP}}$. The percentage price change that passive flows generate is proportional to

$$\frac{1}{S_n}\frac{\partial S_n}{\partial(-\mathrm{MRP})} = \frac{b_n \beta^s}{S_n (r+\beta^s \mathrm{MRP})^2} + \frac{\bar{D}^i_n \beta^i_n}{S_n (r+\beta^i_n \mathrm{MRP})^2}$$

$$= w^s_n \frac{\beta^s}{r+\beta^s \mathrm{MRP}} + w^i_n \frac{\beta^i_n}{r+\beta^i_n \mathrm{MRP}}, \tag{3.5}$$

where $w^s_n \equiv \frac{b_n}{S_n(r+\beta^s \mathrm{MRP})}$ is the fraction of the price accounted for by the systematic component and $w^i_n \equiv \frac{\bar{D}^i_n}{S_n(r+\beta^i_n \mathrm{MRP})}$ is the fraction accounted for by the idiosyncratic component. Since the stock's CAPM beta is $\beta_n = w^s_n \beta^s + w^i_n \beta^i_n$, we can write Equation (3.5) as

$$\frac{1}{S_n}\frac{\partial S_n}{\partial(-\mathrm{MRP})} = \frac{\beta_n}{r+\beta^s \mathrm{MRP}} + w^i_n \beta^i_n \left[\frac{1}{r+\beta^i_n \mathrm{MRP}} - \frac{1}{r+\beta^s \mathrm{MRP}}\right]. \tag{3.6}$$

For small stocks, β^i_n is negligible. Therefore, the second term in Equation (3.6) is negligible and the price effect of passive flows increases in the stocks' CAPM beta β_n and does not depend on stock size. For large stocks, however, β_n^i is non-negligible because these stocks account for a non-negligible fraction of the market portfolio. Therefore, passive flows raise the prices of large stocks above and beyond their effect through the stocks' beta. Intuitively, the present value of idiosyncratic dividends is more sensitive to a drop in MRP, per unit of idiosyncratic beta β_n^i, than the present value of systematic dividends is, per unit of systematic beta β^s. This is because the discount rate for idiosyncratic dividends is lower than for systematic dividends ($\beta_n^i < \beta^s$).

The same mechanism as in the example operates within our model. Setting $\eta_n' = \eta_n$ and $u_n = \hat{u}\eta_n$ for all n in Equation (2.14), we find $\lambda = \frac{1-\hat{u}}{\mu_1+\mu_2}$. Setting $\eta_n' = \eta_n$ and $u_n = \hat{u}\eta_n$ for all n and $\lambda = \frac{1-\hat{u}}{\mu_1+\mu_2}$ in Equation (3.2), we find $\Delta_n = \frac{(1-\phi)\mu_1(1-\hat{u})}{(\mu_1+\mu_2)^2}\eta_n$. Therefore, Equation (3.1) implies that the percentage change in the price of stock n that passive flows generate is

$$\frac{1}{S_{nt}}\frac{dS_{nt}}{d\mu_2} = \frac{(1-\phi)\rho(1-\hat{u})}{(\mu_1+\mu_2)^2 S_{nt}}\left[b_n\left(\sum_{m=1}^N \eta_m b_m\right)(\sigma^s a_1^s)^2\left(\frac{\kappa^s}{r}+D_t^s\right)F^s + \eta_n(\sigma_n^i a_{n1}^i)^2\left(\frac{\kappa_n^i}{r}\bar{D}_n^i + D_{nt}^i\right)F_n^i\right]. \tag{3.7}$$

We next write Equation (3.7) in terms of the CAPM beta of stock n and of the difference in discount rates between systematic and idiosyncratic dividends. Using Equations (2.2), (2.8), and (2.9), we find that the conditional covariance between the return on stock n and the share return on the market portfolio is

$$\mathbb{C}\text{ov}_t\left(dR_{nt}, \sum_{m=1}^N \eta_m dR_{mt}^{sh}\right) = \frac{1}{S_{nt}}\left[b_n\left(\sum_{m=1}^N \eta_m b_m\right)(\sigma^s a_1^s)^2 D_t^s + \eta_n(\sigma_n^i a_{n1}^i)^2 D_{nt}^i\right]. \tag{3.8}$$

Using Equation (3.8), we can write Equation (3.7) as

$$\frac{1}{S_{nt}}\frac{dS_{nt}}{d\mu_2} = \frac{(1-\phi)\rho(1-\hat{u})}{(\mu_1+\mu_2)^2}\left[\left(\frac{\kappa^s}{rD_t^s}+1\right)F^s\mathbb{C}\text{ov}_t\left(dR_{nt}, \sum_{m=1}^N \eta_m dR_{mt}^{sh}\right) + \frac{\eta_n(\sigma_n^i a_{n1}^i)^2}{S_{nt}}\left(\left(\frac{\kappa_n^i}{r}\bar{D}_n^i + D_{nt}^i\right)F_n^i - \left(\frac{\kappa^s}{rD_t^s}+1\right)D_{nt}^i F^s\right)\right]. \tag{3.9}$$

Equation (3.9) is the counterpart within our model of Equation (3.6), with the two terms inside the square bracket in the right-hand side of Equation (3.9) corresponding to the two terms in the right-hand side of Equation (3.6). Proposition 3.2 derives the implications of Equation (3.9).

Proposition 3.2. Suppose $\mathcal{I} = \{1,..,N\}$ and $\#\{\frac{u_m}{\eta_m} : m \in \{1,..,N\}\} = 1$. Suppose that μ_2 increases and μ_1 decreases by an amount equal to a fraction $\phi \in [0,1]$ of the increase in μ_2. When $\phi = 1$, stock prices do not change. When $\phi < 1$, prices increase, with the following properties:

- Consider two small stocks n and n' with $\eta_n, \eta_{n'} \approx 0$. Stock n experiences a larger percentage price increase than stock n' if $\beta_{nt} > \beta_{n't}$.
- Consider a large stock n with $\eta_n \not\approx 0$ and a small stock n' with $\eta_{n'} \approx 0$, and suppose $\beta_{nt} \geq \beta_{n't}$. Stock n experiences a larger percentage price increase than stock n' if

$$\left(\frac{\kappa_n^i}{r}\bar{D}_n^i + D_{nt}^i\right) F_n^i > \left(\frac{\kappa^s}{r D_t^s} + 1\right) D_{nt}^i F^s. \tag{3.10}$$

When passive flows are due to a pure switch from active to passive ($\phi = 1$), stock prices do not change. This is because in the baseline case experts and non-experts hold the market portfolio. When instead passive flows are due, fully or partly, to entry by new investors into the stock market ($\phi < 1$), stock prices increase. For small stocks, the increase is fully described by CAPM beta and does not depend on stock size. This is because Equation (3.9) (and (3.6)) implies that holding CAPM beta constant, size can have an effect only through idiosyncratic beta, but that beta is negligible for small stocks. For large stocks instead, idiosyncratic beta is not negligible and passive flows raise their prices above and beyond their effect through CAPM beta, provided that Condition (3.10) holds. Condition (3.10) concerns the discount rates for systematic and idiosyncratic dividends. When (D_t^s, D_{nt}^i) are equal to their long-run means, Equations (2.12), (2.13), (3.3), and (3.4) imply that Equation (3.10) is equivalent to $a_{n1}^i\left(\frac{\kappa^s}{r} + 1\right) > a_1^s\left(\frac{\kappa^s}{r} + 1\right)$ and thus to the discount rate for idiosyncratic dividends being smaller than for systematic dividends.

We next turn to the case where the index does not include all stocks or where noise traders hold different fractions of shares across stocks. Using Equation (3.8), we can write Equation (3.1) as

$$\begin{aligned}\frac{1}{S_{nt}}\frac{dS_{nt}}{d\mu_2} = \frac{\rho}{\mu_1}\Bigg[&\frac{\sum_{m=1}^N \Delta_m b_m}{\sum_{m=1}^N \eta_m b_m}\left(\frac{\kappa^s}{r D_t^s} + 1\right) F^s \mathbb{C}\text{ov}_t\left(dR_{nt}, \sum_{m=1}^N \eta_m dR_{mt}^{sh}\right)\\ &+ \frac{(\sigma_n^i a_{n1}^i)^2}{S_{nt}}\left(\Delta_n\left(\frac{\kappa_n^i}{r}\bar{D}_n^i + D_{nt}^i\right) F_n^i\right.\\ &\left.- \frac{\sum_{m=1}^N \Delta_m b_m}{\sum_{m=1}^N \eta_m b_m}\eta_n\left(\frac{\kappa^s}{r D_t^s} + 1\right) D_{nt}^i F^s\right)\Bigg],\end{aligned} \tag{3.11}$$

which generalizes Equation (3.9). Proposition 3.3 derives the implications of Equation (3.11). One implication is derived in the special case where noise-trader demand is independent from stocks' other characteristics. Assumption 3.1 defines this independence case.

Assumption 3.1. [Independence]. The market consists of $N = GL$ stocks, which belong to G disjoint groups, each with cardinality L. The values of $(\bar{D}_n, b_n, \kappa_n^i, \bar{D}_n^i, \sigma_n^i, \eta_n, \eta_n')$ are the same across all stocks in any given group $g = 1,..,G$ and are denoted by $(\bar{D}_g, b_g, \kappa_g^i, \bar{D}_g^i, \sigma_g^i, \eta_g, \eta_g')$. The values of u_n differ across those stocks and are $\{\eta_g \hat{u}_\ell\}_{\ell=1,..,L}$, where $\{\hat{u}_\ell\}_{\ell=1,..,L}$ are the same across groups.

In the independence case, all stock characteristics except noise-trader demand are the same across all stocks within each of a number of disjoint groups. The within-group distribution of the fraction of shares that are held by noise traders is the same across groups. Our calibration is made under Assumption 1, with the main difference between groups being stock size.

Proposition 3.3. Suppose $\mathcal{I} \subsetneq \{1,..,N\}$ or $\#\{\frac{u_m}{\eta_m} : m \in \{1,..,N\}\} > 1$. Suppose that μ_2 increases and μ_1 decreases by an amount equal to a fraction $\phi \in [0,1]$ of the increase in μ_2. The resulting stock price changes have the following properties:

- There exists a non-empty interval $[0,\phi_1) \subset [0,1]$ such that for all $\phi \in [0,\phi_1)$, properties are the same as in Proposition 3.2 , except that large stock n must also satisfy $n \in \mathcal{I}$.
- For all $\phi \in [0,1]$, for any large stock n with $\eta_n \not\approx 0$, $n \in \mathcal{I}$ and $n \in \text{argmax}_m \frac{u_m}{\eta_m}$, and for any small stock n' with $\eta_{n'} \approx 0$, stock n experiences a larger percentage price change than stock n' if $\beta_{nt} = \beta_{n't}$ and Condition (3.10) holds.
- When Assumption 3.1 holds and $\mathcal{I} = \{1,..,N\}$, there exists a non-empty interval $(\phi_2, 1] \subset [0,1]$ such that for all $\phi \in (\phi_2, 1]$ and for any two small stocks n and n' with $\eta_n, \eta_{n'} \approx 0$, their prices decrease and stock n experiences a larger percentage price decrease than stock n' if $\beta_{nt} > \beta_{n't}$.

When passive flows are due, fully or mostly, to entry by new investors in the stock market ($\phi \in [0,\phi_1)$), the prices of all stocks increase. As in Proposition 3.2, the price increase for small stocks is fully described by CAPM beta and is larger for higher beta stocks. Unlike in Proposition 3.2, passive flows do not necessarily raise the prices of large stocks above and beyond their effect through beta. They do so, however, for those large stocks that are included in the index. Intuitively, passive flows affect index and non-index stocks differently because of their effect on the present value of idiosyncratic dividends. Only stocks that belong to the index experience an increase in that present value because passive flows lower their idiosyncratic supply and thus the discount rate for idiosyncratic dividends. The effect through idiosyncratic supply is negligible for small stocks but non-negligible for large stocks.

When passive flows are due, fully or mostly, to a switch from active to passive ($\phi \in (\phi_2, 1]$), stock prices can increase or decrease. The price change for small stocks is fully described by CAPM beta. Unlike in the case $\phi \in [0,\phi_1)$

and in Proposition 3.2, prices can decrease, in which case the decrease is larger for higher beta stocks. Moreover, passive flows do not raise the price of all large stocks above and beyond their effect through beta, but do so for those large stocks that are included in the index and are in high demand by noise traders. The prices of other large stocks can rise below the effect through beta and can even drop. Intuitively, a pure switch from active to passive raises the idiosyncratic supply for stocks that are not in the index because they are sold by experts but are not bought by non-experts. It also raises the idiosyncratic supply for stocks that are in low demand by noise traders since experts hold them with a weight larger than in the market portfolio while non-experts hold them with the market weight. As in the case where passive flows are due to entry, the effect through idiosyncratic supply is negligible for small stocks but non-negligible for large stocks.

Our calibrations indicate that the positive effect of passive flows on large stocks that are included in a large-stock index and are in high demand by noise traders overtakes any negative effects on other stocks. As a result, passive flows cause the aggregate market to rise even when they are purely due to a switch from active to passive. Proposition 3.3 does not examine how passive flows affect the aggregate market. The equations in this section provide an intuition, however. Since the discount rate for the idiosyncratic dividends of large stocks in high demand is small, the present value of those stocks' idiosyncratic dividends is highly sensitive to changes in the discount rate, generated by passive flows. The high sensitivity is reflected in the term $F_n^i = \frac{1}{\sqrt{(r+\kappa_n^i)^2 + 4\rho \frac{\eta_n - \mu_2 \lambda \eta_n' - u_n}{\mu_1} (\sigma_n^i)^2}}$ in Equation (3.1) being large because η_n' is equal to η_n rather than to zero (stock n is included in the index) or because u_n is large (stock n is in high demand by noise traders). The large positive effect of passive flows on large stocks in high demand can be reinterpreted as the amplification effect described in the beginning of this paper.[9]

4. Calibration

4.1 Parameter values

The model parameters are the riskless rate r, the number N of stocks, the parameters $(\kappa^s, \bar{D}^s, \sigma^s)$ and $(b_n, \kappa_n^i, \bar{D}_n^i, \sigma_n^i)_{n=1,..,N}$ of the dividend processes, the supply parameters $(\eta_n, \eta_n', u_n)_{n=1,..,N}$, the measures (μ_1, μ_2) of experts and non-experts, and the risk-aversion coefficient ρ.

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9 The amplification effect can be seen formally through Equation (2.10). Passive flows lower the idiosyncratic supply $\frac{\eta_n - \mu_2 \lambda \eta_n' - u_n}{\mu_1}$ of a stock n in high demand. Holding constant a_{n1}^i in the right-hand side of Equation (2.10), this raises a_{n1}^i in the left-hand side. Transposing the rise in a_{n1}^i to the right-hand side generates a further rise in a_{n1}^i in the left-hand side for a stock n that is in high demand and sold short by experts because $\frac{\eta_n - \mu_2 \lambda \eta_n' - u_n}{\mu_1}$ is negative, and so on.

We set the starting values of μ_1 and μ_2 so that their sum $\mu_1+\mu_2$ is one. This is a normalization because we can redefine ρ. We set ρ to one. This is also a normalization because we can redefine the numeraire in the units of which wealth is expressed. Since the dividend flow is normalized by $\bar{D}_n+b_n+\bar{D}^i_n=1$, redefining the numeraire amounts to rescaling the numbers of shares $(\eta_n,\eta'_n,u_n)_{n=1,..,N}$. We set the riskless rate r to 3%.

We set starting values $\mu_1=0.9$ and $\mu_2=0.1$—that is, the measure of experts is nine times that of non-experts. We examine how stock prices change when μ_2 is raised to 0.6—that is, the measure of non-experts rises sixfold. We consider two polar cases for the measure of experts. The first case is when flows into passive funds are entirely due to entry by new investors into the stock market ($\phi=0$). In that case, the measure μ_1 of experts remains equal to 0.9. The second case is when flows into passive funds are entirely due to a switch by investors from active to passive ($\phi=1$). In that case, the total measure $\mu_1+\mu_2$ of experts and non-experts remains equal to one.

We calibrate the number N of stocks and the number η_n of shares of each stock based on the number and size distribution of publicly listed U.S. firms. Axtell (2001) finds that the size distribution of all U.S. firms, with size measured by sales or number of employees, is well approximated by a power law with exponent one.[10] Under that power law, if an interval $[x,\phi x]$ with $\phi>1$ includes a fraction f of firms and their average size is s, then the adjacent interval $\left[\phi x,\phi^2 x\right]$ includes a fraction $\frac{f}{\phi}$ of firms and their average size is ϕs. Motivated by this scaling property, we set $\phi=5$ and assume five size groups. Size group 5, the top group, includes six stocks, each of which is issued in $625\times\eta$ shares. Size group 4 includes 30 ($=5\times 6$) stocks, each of which is issued in $125\times\eta$ ($=\frac{1}{5}\times 625\times\eta$) shares. Size group 3 includes 150 ($=5\times 30$) stocks, each of which is issued in $25\times\eta$ ($=\frac{1}{5}\times 125\times\eta$) shares. Size group 2 includes 750 ($=5\times 150$) stocks, each of which is issued in $5\times\eta$ ($=\frac{1}{5}\times 25\times\eta$) shares. Size group 1, the bottom group, includes 750 stocks, each of which is issued in η ($=\frac{1}{5}\times 5\times\eta$) shares. We drop the scaling property for group 1 to better fit the data.

The five size groups in our calibration are defined based on the aggregate dividends that firms pay to their shareholders. Indeed, since the long-run mean of the dividend flow per share is normalized to one for each firm, the long-run mean of aggregate dividend flow for each firm is equal to the firm's number of shares. Market capitalization varies monotonically across size groups, with its ratio between two stocks in consecutive groups being close to five, as is the case for the number of shares. Constructing the market capitalization ratios in the data as in our calibration, we find values close to five as well.[11]

10 For a survey on power laws and their relevance to economics and finance, see Gabaix (2016).

11 As of April 2, 2024, average market capitalization was $2.175 trillion for the top six publicly listed U.S. firms (Microsoft, Apple, NVIDIA, Alphabet, Amazon, Meta), $379.2 billion for the next 30 firms, $94.14 billion

We consider three cases for index composition. The baseline is when the index includes all stocks and is thus the true market portfolio—that is, $\eta'_n = \eta_n$ for all n. The second case is when the index includes only the stocks in our top three size groups—that is, $\eta'_n = \eta_n$ for the 186 stocks in size groups 3, 4, and 5, and $\eta'_n = 0$ for the 1,500 stocks in size groups 1 and 2. That index can be interpreted as a large-stock index such as the Russell 200 or the S&P500.[12] The third case is when the index includes only the stocks in our bottom three size groups—that is, $\eta'_n = \eta_n$ for the 1,650 firms in size groups 1, 2, and 3, and $\eta'_n = 0$ for the 36 firms in size groups 4 and 5.

We consider two cases for noise-trader demand u_n. The baseline is when u_n is equal to zero for all stocks, and thus there are no noise traders. The second case is when u_n is equal to zero for one-half of the stocks in each size group, and to 30% of the shares issued for the remaining half ($u_n = 30\% \times \eta_n$). The former stocks are the low-demand ones and the latter stocks are the high-demand ones.

We set the mean-reversion parameters κ^s and $\{\kappa^i_n\}_{n=1,..,N}$ to a common value κ. We set the long-run means $\{\bar{D}^i_n\}_{n=1,..,N}$ and diffusion parameters $\{\sigma^i_n\}_{n=1,..,N}$ of the idiosyncratic components to common values $\bar{D}^i$ and σ^i, respectively. The stationary distribution of D^i_{nt} generated by the square-root process in Equation (1.3) is gamma with support $(0,\infty)$ and density

$$f(D^i_{nt}) = \frac{(\beta_i)^{\alpha^i}}{\Gamma(\alpha^i)}(D^i_{nt})^{\alpha^i - 1} e^{-\beta^i D^i_{nt}}, \tag{4.1}$$

where $\alpha^i \equiv \frac{2\kappa \bar{D}^i}{(\sigma^i)^2}$, $\beta^i \equiv \frac{2\kappa}{(\sigma^i)^2}$ and Γ is the Gamma function. The stationary distribution of D^s_t generated by the square-root process in Equation (1.2) is also gamma, with density given by Equation (4.1) in which D^i_{nt} is replaced by D^s_t, α^i by $\alpha^s \equiv \frac{2\kappa \bar{D}^s}{(\sigma^s)^2} = \frac{2\kappa}{(\sigma^s)^2}$, and β^i by $\beta^s \equiv \frac{2\kappa}{(\sigma^s)^2}$. We set $\frac{\sigma^i}{\sqrt{\bar{D}^i}} = \frac{\sigma^s}{\sqrt{\bar{D}^s}} = \sigma^s$. This ensures that the distributions of D^s_t and D^i_{nt} are the same when scaled by their long-run means: $\frac{D^i_{nt}}{\bar{D}^i}$ has the same distribution as $\frac{D^s_t}{\bar{D}^s} = D^s_t$.

We allow for correlation between size and the loading b_n of dividends on the systematic factor. We assume that for stocks in size group $m = 1,..,5$, $b_n = \bar{b} -$

for the next 150 firms, \$16.06 billion for the next 750 firms, and \$2.887 billion for the next 750 firms. The combined market capitalization of all 3,605 publicly listed U.S. firms was \$53.54 trillion. The combined market capitalization of the 1,686 (= 6 + 30 + 150 + 750 + 750) firms in our size groups 1, 2, 3, 4, and 5 was \$52.76 trillion. The market capitalization ratios were 5.74 (= $\frac{2175}{379.2}$) between size groups 5 and 4, 4.03 (= $\frac{379.2}{94.14}$) between size groups 4 and 3, 5.86 (= $\frac{94.14}{16.06}$) between size groups 3 and 2, and 5.56 (= $\frac{16.06}{2.887}$) between size groups 2 and 1. The counterparts of these ratios generated by our model are 4.51, 4.86, 4.97, and 4.99 in the baseline of the constant-b_n calibration, and 5.01, 5.30, 5.46, and 5.54 in the baseline of the varying-b_n calibration. If size group 1 is enlarged to include the remaining 1,919 (=3,605 − 1,686) publicly listed U.S. firms, then the ratio between size groups 2 and 1 in the data jumps up to 14.53. All market capitalization data come from https://companiesmarketcap.com/usa/largest-companies-in-the-usa-by-market-cap/.

[12] While the S&P500 accounts for a larger fraction of market capitalization than an index made of the 186 stocks in our size groups 3, 4, and 5, it leaves out a non-negligible fraction. As of April 2, 2024, the S&P500 accounted for 81.5% of the combined market capitalization of all publicly listed U.S. firms. Our size groups 3, 4, and 5 accounted for 72.0%.

Table 4.1
Price and return moments for $(\mu_1,\mu_2)=(0.9,0.1)$ and the baseline

A. Constant-b_n case

Size group	Price	Expected excess return (%)	Return volatility (%)	CAPM beta	CAPM R^2 (%)
1 (smallest)	12.93	3.89	12.56	1.01	26.18
2	12.91	3.90	12.56	1.01	26.28
3	12.83	3.93	12.56	1.02	26.81
4	12.46	4.07	12.53	1.07	29.32
5 (largest)	11.24	4.62	12.45	1.24	39.78

B. Varying-b_n case

Size group	Price	Expected excess return (%)	Return volatility (%)	CAPM beta	CAPM R^2 (%)
1 (smallest)	10.42	5.34	12.51	1.38	28.82
2	11.54	4.65	11.09	1.19	27.46
3	12.59	4.11	9.93	1.04	26.41
4	13.35	3.76	8.88	0.96	27.52
5 (largest)	13.37	3.72	7.64	0.96	37.04

$(m-3)\Delta b \geq 0$. Varying Δb changes the relationship between size and CAPM beta.

The parameters left to calibrate are $(\kappa, \bar{D}^i, \bar{b}, \Delta b, \sigma^s, \eta)$. We calibrate them based on stocks' unconditional expected excess returns, return variances, CAPM betas, and CAPM R^2s. We use as calibration targets the values of these moments for the starting measures $(\mu_1,\mu_2)=(0.9,0.1)$ and for the baseline where the index includes all stocks and there are no noise traders. The formulas for the moments are in Internet Appendix B. The values of the moments for $(\mu_1,\mu_2)=(0.9,0.1)$ and the baseline are in Table 4.1.

The effects of changing κ on return moments and other numerical results are similar to those of changing the other parameters. We set $\kappa=4\%$. The values of $(\bar{D}^i, \bar{b}, \Delta b)$ must satisfy $\bar{b}+(m-3)\Delta b+\bar{D}^i \leq 1$ for all $m=1,..,5$ because of $\bar{D}_n \geq 0$ and the normalization $\bar{D}_n+b_n+\bar{D}^i=1$. Inequality $\bar{b}+(m-3)\Delta b+\bar{D}^i \leq 1$ for all $m=1,..,5$ is equivalent to $\bar{b}+2|\Delta b|+\bar{D}^i \leq 1$. We assume that the latter inequality holds as an equality. This minimizes the constant component $\bar{D}_n \geq 0$, which becomes zero for the largest-b_n stocks. Minimizing $\bar{D}_n$ maximizes return variances, bringing them closer to their empirical counterparts as we explain later.

We consider two cases for Δb. The first case is when $\Delta b=0$ and thus the loading b_n of dividends on the systematic factor is the same for all stocks. In this constant-b_n case, CAPM beta increases monotonically with size because the contribution of idiosyncratic dividends to beta is larger for larger stocks. While a positive relationship between size and beta is counterfactual, as the empirical relationship is negative (Fama and French 1992), the constant-b_n case serves as a useful benchmark. Our assumption that the constant component of dividends is zero for the largest-b_n stocks implies that it is zero for all stocks in the constant-b_n case, and thus plays no role. The second case is when Δb takes the positive value $\Delta b=0.04$ that generates a negative relationship between size and beta approximating the empirical one. In this varying-b_n case, beta is 1.38 for the stocks in size group 1 and 0.96 for the stocks in size group 5. Constructing the same size groups in the data as in our model, we find that average beta is 1.26 for size group 1 and 0.93 for size group 5 when stocks within groups are weighed according to their market capitalization.[13]

We calibrate the relative size of $\bar{b}$ and $\bar{D}^i$ based on CAPM R^2. CAPM R^2 in the data averages to 29.71% across the stocks in all size groups when they are weighted according to their market capitalization.[14] In the constant-b_n case, this R^2 is achieved by setting $\bar{b}=0.75$ and $\bar{D}^i=0.25$. In the varying-b_n case, this is achieved for $\bar{b}=0.725$ and $\bar{D}^i=0.195$.

We calibrate the supply parameter η based on stocks' expected excess returns. We target expected returns in excess of the riskless rate to average 4% across the stocks in all size groups when they are weighted according to their market capitalization. In the constant-b_n case, this is achieved for $\eta=0.00004$. In the varying-b_n case, this is achieved for $\eta=0.00007$.

We calibrate the diffusion parameter σ^s based on stocks' return variances. Raising σ^s (and σ^i through $\frac{\sigma^i}{\sqrt{\bar{D}^i}}=\sigma^s$) has a non-monotone effect on variances. For given values of D_t^s and $\{D_{nt}^i\}_{n=1,..,N}$, variances rise. At the same time, the stationary distributions of D_t^s and $\{D_{nt}^i\}_{n=1,..,N}$ shift weight toward very small or very large values, for which conditional variances are low under the square-root specification.[15] One approach is to set σ^s to the value that maximizes return variances. The resulting variances are comparable to their empirical counterparts for large firms in the constant-b_n case and are somewhat below them in the varying-b_n case. The resulting prices are overly low, however, relative to the calibrated expected returns. Another approach is to use a lower value for σ^s, undershooting return variances, but obtaining prices more in line with expected returns. The two approaches yield similar results for the effects of passive flows. We follow the former approach in Internet Appendix E.1, setting $s^s=2.2$, which is the value in the varying-b_n case that maximizes the average return variance across stocks in all size groups when they are weighted according to their market capitalization. We follow the latter approach in the rest of this section, setting $s^s=0.5$.[16]

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[13] In each quarter during the sample period of our empirical exercise in Section 5, we sort the 1,686 largest stocks into five size groups as in our model. We regress the quarterly value-weighted excess returns on the resulting five portfolios on the excess return on the market (CRSP index) to compute CAPM betas.

[14] We construct the five size groups as in the CAPM beta exercise, compute R^2 for each stock from a CAPM regression with monthly returns and a five-year lookback window, and average across stocks using market-capitalization weights.

[15] For small values of D_t^s and $\{D_{nt}^i\}_{n=1,..,KN}$, return variances per share are small but share prices do not converge to zero because of the mean-reversion of D_t^s and $\{D_{nt}^i\}_{n=1,..,KN}$. Therefore, return variances converge to zero. For large values of D_t^s and $\{D_{nt}^i\}_{n=1,..,KN}$, return variances converge to zero because return variances per share are proportional to D_t^s and $\{D_{nt}^i\}_{n=1,..,KN}$ and share prices are affine in these variables.

[16] For $s^s=2.2$, the average price across the stocks in all size groups when they are weighted according to the number of shares issued is 4.29 in the constant-b_n case and 5.16 in the varying-b_n case. In comparison, discounting

Table 4.2
Percentage price change caused by passive flows in the baseline

	Entry into the stock market		Switch from active to passive	
Size group	Constant-b_n	Varying-b_n	Constant-b_n	Varying-b_n
1 (smallest)	7.03	7.67	0	0
2	7.08	6.63	0	0
3	7.34	5.99	0	0
4	8.45	6.17	0	0
5 (largest)	11.78	7.53	0	0

Table 4.1 shows the unconditional average of the price and the unconditional return moments for $(\mu_1, \mu_2) = (0.9, 0.1)$ and the baseline, in the constant-b_n case (panel A) and the varying-b_n case (panel B). When moving from the smallest to the largest size group, expected excess return and CAPM beta rise in the constant-b_n case but decline in the varying-b_n case. Stocks in size group 5 have the largest CAPM R^2, even in the varying-b_n case where their CAPM beta is the smallest. This is because Proposition 2.1 implies that stock prices are less sensitive to idiosyncratic dividend shocks when idiosyncratic supply is large.

4.2 Passive flows and stock prices: Calibration results

4.2.1 Baseline. Table 4.2 shows how flows into passive funds affect stock prices in the baseline. We compute the percentage change of the unconditional average of the price. Computing instead the unconditional average of the percentage change yields similar results. Since the price is linear in D_t^s and D_{nt}^i, we can compute its unconditional average by setting the systematic component D_t^s and the idiosyncratic component D_{nt}^i of dividends to their long-run means, $\bar{D}^s = 1$ and $\bar{D}_n^i$.

The second and third columns of Table 4.2 report the percentage price change when μ_2 is raised to 0.6 and μ_1 is held equal to 0.9. Passive flows in these columns are due entirely to entry by new investors into the stock market ($\phi = 0$). The second column corresponds to the constant-b_n case and the third column to the varying-b_n case. The fourth and fifth columns are counterparts of the second and third columns when μ_2 is raised to 0.6 and μ_1 is lowered to 0.4. Passive flows in these columns are due entirely to a switch by investors from active to passive ($\phi = 1$).

Consistent with Proposition 3.1, passive flows do not affect stock prices when they are due to a switch by investors from active to passive, and raise prices when they are due to entry by new investors into the stock market.

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expected dividends of one at the sum of the riskless rate of 3% plus the average expected excess return of 4% yields $\frac{1}{7\%} = 14.29$. The discrepancy arises because of the expected returns' time variation. For $\sigma^s = 2.2$, the stationary distributions of D_t^s and $\{D_{nt}^i\}_{n=1,..,N}$ give high weight to extreme values. Moreover, expected excess returns are close to zero for small values of D_t^s and $\{D_{nt}^i\}_{n=1,..,N}$, but increase significantly away from zero, and average prices are primarily determined by expected returns away from zero. The discrepancy is significantly smaller for $s^s = 0.5$ because the average price is 12.39 in the constant-b_n case and 12.61 in the varying-b_n case.

When passive flows are due to entry, the percentage price increase that they generate is larger for larger stocks in the constant-b_n case, and is a U-shaped function of stock size in the varying-b_n case. These results as well are consistent with Proposition 3.1. Indeed, the proposition shows that when $\phi<1$, the effect of passive flows is increasing in CAPM beta and is larger for large stocks holding beta constant. In the constant-b_n case, beta increases with size, so the two effects work in the same direction, causing the effect of passive flows to increase with size. In the variable-b_n case, beta decreases with size. Therefore, the effect of passive flows decreases with size for small stocks but can increase for large stocks. Table 4.2 shows that the effect of size dominates that of beta for size groups 4 and especially 5.[17]

To illustrate why the effect of size can dominate that of beta, we return to Equations (3.6) and (3.9). When $\kappa^s=\kappa_n^i=\kappa$ and (D_t^s, D_{nt}^i) are equal to their long-run means, we can write Equation (3.9) as

$$\frac{1}{S_{nt}}\frac{dS_{nt}}{d\mu_2}=\frac{(1-\phi)\rho(1-\hat{u})(\kappa+r)F^s}{(\mu_1+\mu_2)^2 r}\mathbb{C}\mathrm{ov}_t\left(dR_{nt},\sum_{m=1}^{N}\eta_m dR_{mt}^{sh}\right)\left(1+\gamma_n^i\frac{F_n^i-F^s}{F^s}\right), \tag{4.2}$$

where

$$\gamma_n^i\equiv\frac{\frac{\eta_n(\sigma_n^i a_{n1}^i)^2\bar{D}_n^i}{S_{nt}}}{\mathbb{C}\mathrm{ov}_t\left(dR_{nt},\sum_{m=1}^{N}\eta_m dR_{mt}^{sh}\right)}$$

is the fraction of stock n's CAPM beta that is driven by stock n's idiosyncratic dividends. The percentage price rise for stock n exceeds that for stock n' if

$$\frac{1+\gamma_n^i\frac{F_n^i-F^s}{F^s}}{1+\gamma_{n'}^i\frac{F_{n'}^i-F^s}{F^s}}>\frac{\mathbb{C}\mathrm{ov}_t\left(dR_{n't},\sum_{m=1}^{N}\eta_m dR_{mt}^{sh}\right)}{\mathbb{C}\mathrm{ov}_t\left(dR_{nt},\sum_{m=1}^{N}\eta_m dR_{mt}^{sh}\right)}. \tag{4.3}$$

When stock n is larger than stock n' and has smaller beta, the effect of size dominates that of beta if the left-hand side of Equation (4.3) exceeds the right-hand side, which exceeds one. In the varying-b_n case, the fraction γ_n^i of beta that is driven by idiosyncratic dividends is 8.04% for stocks in size group 5 and 2.43%, 0.53%, 0.10%, and 0.02% for stocks in size groups 4, 3, 2, and 1,

[17] For brevity, we report only price changes in Section 4, not changes in expected returns. Changes in expected returns follow broadly similar patterns to price changes. In Table 4.2, for example, expected returns drop when passive flows are due to entry, with the drop being an increasing function of size in the constant-b_n case and a U-shaped function in the varying-b_n case. The U-shape for expected returns is less pronounced relative to that for prices for large firms. Indeed, because expected return in the varying-b_n case is lower for large firms, a given price rise for those firms is triggered by a smaller drop in expected return than for smaller firms. The drop in expected return is 0.70% for size group 1, 0.57% for size group 2, 0.47% for size group 3, 0.44% for size group 4, and 0.49% for size group 5. The drop in the market risk premium is 0.5%, and in the constant-b_n case it is 0.6%.

respectively. The ratio $\frac{a^i_{n1}}{a^s_1}$ of the discount rate for systematic dividends to that for idiosyncratic dividends takes the values 5.15, 6.33, 6.72, 6.81, and 6.83 for stocks in size groups 5, 4, 3, 2, and 1, respectively. The corresponding ratio $\frac{F^i_n - F^s}{F^s}$ takes the values 6.66, 9.92, 11.26, 11.59, and 11.66. Therefore, the term $\gamma^i_n \frac{F^i_n - F^s}{F^s}$ is 53.52% (=8.04% × 6.66) for stocks in size group 5 and 24.06%, 5.94%, 1.20%, and 0.23% for stocks in size groups 4, 3, 2, and 1, respectively. The left-hand side of Equation (4.3) for a stock n in size group 5 and a stock n' in size group 3 is thus 1.45 ($=\frac{1+53.52\%}{1+5.94\%}$) and exceeds the ratio of betas of stock n' to stock n in the right-hand side.

The effect of passive flows on the aggregate market in Table 4.2 translates into a demand elasticity higher than in the literature. Suppose that the measure μ_2 of non-experts increases from 0.1 to 0.6, holding the measure μ_1 of experts equal to 0.9. In the constant-b_n case, the aggregate market rises by 8.48% and non-experts' holdings (equal to $\mu_2\lambda$ times the value of the market) increase by 33.39% of the market's initial value. The resulting elasticity is 3.93 ($=\frac{33.39}{8.48}$). In the varying-b_n case, the elasticity is 4.92. By contrast, Gabaix and Koijen (2021) estimate an elasticity of 0.2 for the aggregate market, while the literature on index additions estimates elasticities ranging from 0.4 to 4 for individual firms. Our model might be generating a high elasticity for two reasons. First, the fraction of truly active investors might be smaller than in our calibration because many active funds in practice have constraints limiting their deviations from benchmark indices. Second, the elasticity estimates in the literature mostly concern short-run elasticities, while the elasticities in our model are long-run.

4.2.2 Partial index. Table 4.3 shows how flows into passive funds affect stock prices when the index includes only the stocks in the top three size groups (panel A) and when it includes only the stocks in the bottom three size groups (panel B). The columns are as in Table 4.2.

When passive flows are due to entry by new investors into the stock market, their effect on small stocks is approximately independent of index composition and same as in the baseline. The effect on large stocks, by contrast, depends significantly on index composition. Stocks in size group 4 and especially 5 rise significantly more when the index includes only size groups 3, 4, and 5 than when it includes only size groups 1, 2, and 3, with the baseline effect being in-between. The comparisons to the baseline carry through to the case where passive flows are due to a switch from active to passive. The effect on small stocks is approximately independent of index composition and equal to zero, as in the baseline. By contrast, stocks in size group 4 and especially 5 rise significantly when the index includes only size groups 3, 4, and 5, and drop significantly when it includes only size groups 1, 2, and 3. These results reflect the result of Proposition 3.3 that the effects of passive flows depend on index inclusion for large stocks but not for small stocks.

Table 4.3
Percentage price change caused by passive flows into a partial index

A. Index includes only top three size groups

	Entry into the stock market		Switch from active to passive	
Size group	Constant-b_n	Varying-b_n	Constant-b_n	Varying-b_n
1 (smallest)	6.90	7.50	−0.42	−0.56
2	6.91	6.44	−0.60	−0.69
3	7.32	6.00	0.04	0.13
4	8.80	6.59	1.50	1.67
5 (largest)	13.43	9.03	5.98	5.32

B. Index includes only bottom three size groups

	Entry into the stock market		Switch from active to passive	
Size group	Constant-b_n	Varying-b_n	Constant-b_n	Varying-b_n
1 (smallest)	7.02	7.66	−0.02	−0.01
2	7.11	6.67	0.15	0.17
3	7.56	6.21	0.97	0.93
4	7.29	5.09	−4.12	−3.64
5 (largest)	8.13	4.80	−9.54	−6.58

Table 4.3 yields two additional implications. First, passive flows have a disproportionately large effect (relative to simple CAPM logic) on the largest stocks in an index only when these stocks are also the largest in the economy. Indeed, the rising part of the U-shape shown in Table 4.2 in the varying-b_n case does not arise among index stocks when the index includes only size groups 1, 2, and 3, but arises when the index includes only size groups 3, 4, and 5.

The second implication of Table 4.3 is that passive flows into an index that does not include all stocks affect the valuation of the aggregate market even when the flows are a pure switch from active to passive. A pure switch from active to the passive large-stock index raises the aggregate market by 1.49% in the constant-b_n case and 1.63% in the varying-b_n case. A pure switch from active to the passive small-stock index lowers the aggregate market by 2.75% in the constant-b_n case and 2.31% in the varying-b_n case. These movements arise because the switch has negligible effects on small stocks but significant effects on large stocks.

4.2.3 Noise traders. Table 4.4 shows how flows into passive funds affect stock prices when stocks differ in noise-trader demand. There are 10 groups of stocks: five size groups and two demand subgroups within each size group. The columns are as in Table 4.2 with the addition of a column that indicates whether a stock is in high or low demand.

The effects of passive flows are approximately independent of noise-trader demand for small stocks. For large stocks instead, especially in size group 5, passive flows have larger effects on high-demand stocks. These results reflect the result of Proposition 3.3 that the effects of passive flows depend on noise-trader demand for large stocks but not for small stocks.

Table 4.4
Percentage price change caused by passive flows with noise traders

		Entry into the stock market		Switch from active to passive	
Size group	Noise-trader demand	Constant-b_n	Varying-b_n	Constant-b_n	Varying-b_n
1 (smallest)	Low	7.27	7.95	−0.02	−0.02
	High	7.27	7.95	−0.00	−0.01
2	Low	7.32	6.89	−0.04	−0.05
	High	7.31	6.89	0.02	0.03
3	Low	7.54	6.20	−0.17	−0.18
	High	7.52	6.18	0.15	0.16
4	Low	8.49	6.22	−0.68	−0.63
	High	8.47	6.25	0.73	0.70
5 (largest)	Low	11.31	7.24	−1.90	−1.38
	High	11.71	7.78	2.59	2.03

Table 4.5
Percentage price change caused by passive flows into a partial index with noise traders

		Entry into the stock market		Switch from active to passive	
Size group	Noise-trader demand	Constant-b_n	Varying-b_n	Constant-b_n	Varying-b_n
1 (smallest)	Low	7.15	7.80	−0.43	−0.59
	High	7.15	7.79	−0.42	−0.57
2	Low	7.16	6.72	−0.60	−0.71
	High	7.16	6.71	−0.54	−0.64
3	Low	7.51	6.19	−0.21	−0.16
	High	7.49	6.18	0.13	0.21
4	Low	8.76	6.55	0.40	0.57
	High	8.77	6.61	2.08	2.28
5 (largest)	Low	12.56	8.37	2.05	1.99
	High	13.37	9.39	10.03	9.58

Table 4.4 implies additionally that passive flows in the presence of noise traders raise the aggregate market even when they are a pure switch from active to passive. The positive effects on large high-demand stocks thus exceed the negative effects on large low-demand stocks. Intuitively, because the discount rate for idiosyncratic dividends is lower for the high-demand stocks, the present value of their idiosyncratic dividends is more sensitive to changes in the discount rate. The effects on the aggregate market are smaller than in the case of a partial index: a pure switch from active to passive raises the market by 0.09% in both the constant-b_n and the varying-b_n case.

The effects of passive flows on large high-demand stocks become particularly large and asymmetric when passive flows are into a large-stock index. This is shown in Table 4.5, in which the index is assumed to include only the stocks in the top three size groups. The columns are as in Table 4.4.

In both the constant-b_n and the varying-b_n case, a pure switch from active to passive has large positive effects on high-demand stocks in size group 5, and significantly smaller effects on all other stocks. Because of the asymmetrically large effects on the large high-demand stocks, the aggregate market rises, by 1.47% in the constant-b_n and 1.68% in the varying-b_n case.

Table 4.6
Change in idiosyncratic volatility caused by passive flows from active

		All-stock index		Large-stock index	
Size group	Noise-trader demand	Constant-b_n	Varying-b_n	Constant-b_n	Varying-b_n
1 (smallest)	Low	0.00	0.00	0.06	0.09
	High	0.00	0.00	0.06	0.09
2	Low	0.00	0.00	0.05	0.06
	High	0.00	0.00	0.05	0.06
3	Low	0.00	−0.01	0.07	0.07
	High	0.00	0.01	0.08	0.10
4	Low	−0.03	−0.05	0.10	0.12
	High	0.03	0.05	0.16	0.24
5 (largest)	Low	−0.08	−0.12	0.18	0.24
	High	0.11	0.16	0.43	0.73

4.2.4 Return volatility. Since passive flows raise the present value of the idiosyncratic component of dividends of large stocks in high demand, they cause movements to that component to become larger. Those movements also become larger relative to the stocks' price provided that the price does not increase by as much. When passive flows are due to a switch from active to passive, the change in the market risk premium is small and so is the change in the present value of the systematic component of dividends. Therefore, the idiosyncratic volatility of large stocks in high demand rises. When instead passive flows are due to entry by new investors in the stock market, the present value of the systematic component of dividends rises significantly, and idiosyncratic volatility can fall. In both cases, however, the idiosyncratic volatility of large stocks in high demand rises more (or falls less) than for small stocks because passive flows do not affect the present value of the idiosyncratic component of small stocks' dividends.

Table 4.6 shows the effect of passive flows on idiosyncratic volatility when flows are due to a switch from active to passive. The table confirms that the idiosyncratic volatility of large stocks in high demand rises more than for other stocks, and especially so when the index is a large-stock one. Idiosyncratic volatility averaged across size groups also rises more for large stocks. Table E.6 in Internet Appendix E.2 is the counterpart of Table 4.6 when flows are due to entry by new investors in the stock market. Idiosyncratic volatility can rise or fall, but rises more (or falls less) for large stocks.

5. Empirical Evidence

In this section we present tests of our theory and relate our results to empirical findings in the literature. We take the index to be the S&P500 and flows to be into U.S. listed index mutual funds and ETFs tracking it. The S&P500 index is the most widely tracked by passive funds invested in U.S. stocks: index mutual funds tracking the S&P500 account for 47% to 87% of the assets of all index mutual funds invested in U.S. stocks in our sample. We refer to index mutual funds and ETFs tracking the S&P500 as S&P500 index funds. In an additional test, we repeat our analysis for the S&P600 index, which is made up of small stocks.

5.1 Data and descriptive statistics

Our data on stock returns and market capitalization come from the Center for Research in Security Prices (CRSP). Our data on the composition of the S&P500 index come from CRSP and on the composition of the S&P600 index from Siblis Research. Our data on net assets of S&P500 index mutual funds come from the Investment Company Institute (ICI). Our data on net assets of S&P500 index ETFs and of S&P600 index mutual funds and ETFs come from CRSP. We include in our analysis only plain-vanilla ETFs, excluding alternative ETFs such as leveraged ETFs, inverse ETFs, and buffered ETFs. Our S&P500 index ETF sample consists of the SPDR S&P500 ETF Trust, the iShares Core S&P500 ETF, and the Vanguard S&P500 Index Fund ETF, which collectively account for almost all of the plain-vanilla S&P500 index ETF market. Our S&P500 sample begins in the second quarter of 1996 and ends in the fourth quarter of 2020. Our S&P600 sample begins in the fourth quarter of 2001 and ends in the fourth quarter of 2020.

Table 5.1 reports descriptive statistics. The descriptive statistics in panel A concern aggregate variables, measured at a quarterly frequency. The descriptive statistics in panel B concern a firm-level variable, measured at a quarterly frequency. All variables except VIX and $\log(Vol_{Idio})$ are multiplied by 100.

The first six rows in panel A concern quarterly returns on portfolios of large stocks in the S&P500 index in excess of the index return, and the seventh row concerns the index return. We compute the excess return on the portfolio of the top 10 firms in the S&P500 according to market capitalization, the top 50 firms, the top 100 firms, the top 150 firms, and the top 200 firms. We measure market capitalization at the end of the previous quarter. We compute value-weighted returns except in the case of the top 50 firms where we also compute equally-weighted returns as a robustness check.

The eighth row concerns flows into S&P500 index funds. We measure these flows in any given quarter by the ratio of S&P500 index fund net assets to index market capitalization (i.e., combined capitalization of all S&P500 stocks) minus the same ratio in the previous quarter:

$$PassiveFlow_{SP500,t} = \frac{\$S\&P500IndexAssets_t}{\$S\&P500IndexCap_t} - \frac{\$S\&P500IndexAssets_{t-1}}{\$S\&P500IndexCap_{t-1}}.$$

The mean of passive flow is 0.05% quarterly. Cumulating over the 99 quarters of our sample, we find that an extra 4.95% of market capitalization is held by S&P500 index funds at the end of our sample relative to the beginning.

The 9th and 10th rows concern quarterly returns on the portfolio of the top 60 firms in the S&P600 index in excess of the index return, and the 11th row concerns the index return. We compute both value- and equally-weighted returns on the portfolio of the top 60 firms. The top 60 firms in the S&P600 are

Table 5.1
Descriptive statistics

	A. Aggregate Variables							
	Mean	Std. dev.	25th pctl.	50th pctl.	75th pctl.	Skewness	Exc. kurt.	N
$R^{Exc}_{Top10,SP500}$	−0.02	3.86	−2.04	−0.45	2.59	−0.04	0.39	99
$R^{Exc}_{Top50EW,SP500}$	−0.15	1.56	−1.07	−0.39	0.72	0.51	0.95	99
$R^{Exc}_{Top50,SP500}$	−0.17	1.86	−1.27	−0.20	1.09	−0.16	0.50	99
$R^{Exc}_{Top100,SP500}$	−0.17	1.28	−0.91	−0.23	0.60	−0.61	2.39	99
$R^{Exc}_{Top150,SP500}$	−0.19	0.95	−0.69	−0.19	0.42	−0.49	1.76	99
$R^{Exc}_{Top200,SP500}$	−0.17	0.78	−0.61	−0.19	0.37	−0.47	1.28	99
R_{SP500}	2.68	8.50	−0.77	3.41	7.60	−0.56	0.55	99
$PassiveFlow_{SP500}$	0.05	0.09	0.01	0.05	0.10	0.33	3.62	99
$R^{Exc}_{Top60EW,SP600}$	−0.05	3.41	−1.30	0.08	1.55	−0.04	2.49	77
$R^{Exc}_{Top60,SP600}$	−0.12	3.89	−1.68	0.27	1.97	−0.54	4.19	77
R_{SP600}	3.14	9.97	−0.32	3.99	8.17	−0.63	1.35	77
$PassiveFlow_{SP600}$	0.04	0.11	−0.01	0.03	0.09	−0.34	3.99	77
VIX	20.36	7.59	14.57	19.31	24.92	1.80	6.03	99
B. Firm-Level Variables For All S&P500 Firms								
	Mean	Std. dev.	25th pctl.	50th pctl.	75th pctl.	Skewness	Exc. kurt.	N
$\log(Vol_{Idio})$	−4.28	0.50	−4.63	−4.31	−3.95	0.35	0.40	46,831

the counterpart of the top 50 firms in the S&P500 in the sense of constituting the top size decile. The 12th row concerns flows into S&P600 index funds. The 13th row concerns VIX, the CBOE volatility index.

The single row in panel B concerns the natural logarithm of idiosyncratic volatility for all S&P500 stocks. We measure idiosyncratic volatility by the quarterly standard deviation of daily residual stock returns from the Fama-French three-factor model.

5.2 Tests

Table 5.2 reports the results from regressing the excess returns on S&P500 large-stock portfolios on passive flows into that index. Results in panel A concern the portfolio of the top 50 firms, value- and equally-weighted, with and without controls. Results in panel B concern all large-stock portfolios, value-weighted, with controls. Controls are the S&P500 return, the one-quarter lagged S&P500 return, and VIX.

For ease of interpretation, we standardize $PassiveFlow_{SP500}$ to a mean of zero and a standard deviation of one. We denote the resulting variable with a hat—that is, $\widehat{PassiveFlow}_{SP500}$. The t-statistics, in parentheses, are based on Newey-West heteroscedasticity- and autocorrelation-consistent standard errors with three lags. Our findings are robust to increasing the number of lags.

Table 5.2
Passive flows into the S&P500 and excess returns on S&P500 large-stock portfolios

A. Top 50 firms

Variables	$R^{Exc}_{Top50EW,SP500}$	$R^{Exc}_{Top50,SP500}$	$R^{Exc}_{Top50EW,SP500}$	$R^{Exc}_{Top50,SP500}$
$\widehat{PassiveFlow}_{SP500}$	0.00557	0.00553	0.00531	0.00528
	(3.65)	(3.69)	(4.19)	(3.66)
Constant	−0.00150	−0.00168	−0.000253	−0.00137
	(−0.92)	(−0.80)	(−0.12)	(−0.54)
Observations	99	99	99	99
Controls	N	N	Y	Y
Adjusted R^2	0.127	0.088	0.210	0.125

B. All large-stock portfolios

Variables	$R^{Exc}_{Top10,SP500}$	$R^{Exc}_{Top50,SP500}$	$R^{Exc}_{Top100,SP500}$	$R^{Exc}_{Top150,SP500}$	$R^{Exc}_{Top200,SP500}$
$\widehat{PassiveFlow}_{SP500}$	0.00687	0.00528	0.00303	0.00208	0.00145
	(2.46)	(3.66)	(3.02)	(2.28)	(1.64)
Constant	−0.00156	−0.00137	−0.00177	−0.00189	−0.00149
	(−0.32)	(−0.54)	(−1.00)	(−1.40)	(−1.34)
Observations	99	99	99	99	99
Controls	Y	Y	Y	Y	Y
Adjusted R^2	0.049	0.125	0.105	0.124	0.125

Consistent with our model, the relationship between passive flows and excess returns on large stocks is positive and significant economically and statistically. Panel A shows that a one-standard-deviation increase in $PassiveFlow_{SP500}$ is associated with an increase in the quarterly excess return on the top-50 firm portfolio by an amount ranging from 0.528% to 0.557%, depending on whether returns are value- or equally-weighted and controls are added or not. This is approximately one-third of the quarterly standard deviation of excess returns in Table 5.1. The t-statistic ranges from 3.65 to 4.19. Panel B shows that the effect of $PassiveFlow_{SP500}$ becomes strongest when limiting the large-stock portfolio to the largest firms. A one-standard-deviation increase in $PassiveFlow_{SP500}$ is associated with an increase in the quarterly excess return on the value-weighted portfolio of the top 200 firms by 0.145%, the top 150 firms by 0.208%, the top 100 firms by 0.303%, the top 50 firms by 0.528%, and the top 10 firms by 0.687%.

Converting our quarterly estimates to cumulative estimates over the length of our sample yields large effects. Recall from Table 5.1 that the mean and standard deviation of $PassiveFlow_{SP500}$ are 0.05% and 0.09%, respectively. Since our sample comprises 99 quarters, the cumulative effect of $PassiveFlow_{SP500}$ on the excess return on the value-weighted top-50 firm portfolio is $0.528\% \times \frac{0.05\%}{0.09\%} \times 99 = 29.04\%$. According to this estimate, the rise in passive investing over the past 25 years caused a firm that was in the top 50 of the S&P500 index during the entire period to rise by 29% more than the index.

The estimated 29% effect of passive flows in Table 5.2 is larger than in our calibration. For example, the difference between the return on size group 5 and the average return on size groups 3, 4, and 5 in Tables 4.2–4.5 ranges from zero (Table 4.2, switch from active to passive, all firms in index) to 4% (Table 4.5, switch from active to passive, size groups 3–5 in index). The discrepancy might be arising for the same two reasons mentioned in the context of elasticities in Section 4.2. First, the fraction of truly active investors might be smaller than in our calibration. Second, the 30% estimate concerns a contemporaneous effect of passive flows, which can partly mean-revert.

The finding in Table 5.2 that passive flows raise the stock prices of the largest firms the most is consistent with other findings in the literature. Ben-David, Franzoni, and Moussawi (2018) find that increases in a firm's ownership by ETFs have significantly larger effects on the firms in the S&P500 than on the smaller firms in the Russell 3000 (Table IV). Haddad, Huebner, and Loualiche (2025) find that demand elasticities are smaller for large firms than for smaller firms (Figure 3), implying that an increase in demand proportional to firms' market capitalization causes the stocks of large firms to rise the most.

We corroborate the findings in Table 5.2 through two robustness tests, reported in Internet Appendix E.3. First, we regress changes in S&P500 index concentration on passive flows into that index. We use three measures of concentration: the combined portfolio weight of the stocks of the top 10 firms in the index, the standard deviation of index weights across all index firms, and the Herfindahl index of index weights across all index firms. Consistent with our model, the relationship between passive flows and changes in concentration is positive and significant economically and statistically. Second, we use a beginning-of-month dummy as a proxy to capture exogenous variation in passive flows. Since many U.S. households invest a fraction of their monthly paychecks (together with the contributions from their employers) in passive funds through retirement plans such as 401(K), passive flows increase at the beginning of each month. Consistent with our model, the returns on S&P500 large-stock portfolios rise more than the index at the beginning of each month, with the effect becoming strongest when limiting the large-stock portfolio to the largest firms.[18]

We test three additional predictions of our model. The first prediction is that passive flows should raise the idiosyncratic return volatility of the largest firms in the economy more than of smaller firms (Section 4.2.4). We test this prediction by performing panel regressions of the idiosyncratic volatility of all S&P500 firms on one-quarter-lagged passive flows interacted with a large firm indicator. The indicator is one if a firm belongs to the top 50 and zero otherwise. As additional variables in the regressions we include the two constituents of

[18] Beginning-of-month passive flows can generate return predictability even though they themselves are predictable, provided that agents are uncertain about their magnitude. Vayanos and Woolley (2013) show theoretically that predictable flows generate return predictability in a rational model of return momentum and reversal.

Table 5.3
Passive flows into the S&P500 and idiosyncratic return volatility of S&P500 stocks

	$\log(Vol_{Idio})$	$\log(Vol_{Idio})$
L.$PassiveFlow_{SP500} \times Top50$	19.32	18.46
	(2.53)	(2.45)
L.$PassiveFlow_{SP500}$	20.63	
	(1.21)	
L.$Top50$	−0.0477	−0.0671
	(−2.86)	(−4.83)
Observations	45,737	45,737
Controls	Y	Y
Firm fixed effects	Y	Y
Time fixed effects	N	Y
Adjusted R^2	0.601	0.712

the interaction term, the one-quarter-lagged index return, the logarithm of one-quarter-lagged idiosyncratic volatility, and firm fixed effects. Alternatively, we introduce time fixed effects to absorb the time-series variation, and drop lagged passive flows and index return. We conservatively double-cluster standard errors by firm and time. The regression results are in Table 5.3.

Consistent with our model, passive flows more strongly affect the idiosyncratic return volatility of the largest firms, and this effect is significant economically and statistically. An one-standard-deviation increase in $PassiveFlow_{SP500}$ is associated with an increase in idiosyncratic volatility by 1.86% (= 20.63 × 0.09%) for firms outside the top 50, and this effect approximately doubles to 3.60% (= (19.32 + 20.63) × 0.09%) for firms in the top 50. Moreover, the incremental effect for large firms is statistically significant, while the effect for other firms is not.

The second prediction is that passive flows into an index can disproportionately raise the stock prices of the index's largest firms only when these firms are also the largest in the economy (Section 4.2.2). We test this prediction by repeating the analysis in panel A of Table 5.2 for the S&P600. The regression results are in Table 5.4. Consistent with our model, the relationship between passive flows and excess returns on large stocks in the S&P600 is statistically insignificant.

The third prediction is that the idiosyncratic beta of large firms is positive and non-negligible, while that of smaller firms is negligible (Section 3). We test this prediction in Internet Appendix E.3 by regressing the cumulative abnormal return of S&P500 stocks around earnings announcements on the market return. We focus on earnings announcements because they can reflect shocks to the idiosyncratic component of dividends, and we use the abnormal rather than the full return to better isolate those shocks. The average idiosyncratic beta of the top 50 firms in the S&P500 ranges from 0.0821 to 0.0877 and is statistically significant. The average idiosyncratic beta of the bottom 50 firms is more than 20 times smaller and is statistically insignificant.

Table 5.4
Passive flows into the S&P600 and excess returns on S&P600 large-stock portfolios

Variables	$R^{Exc}_{Top60EW,S\&P600}$	$R^{Exc}_{Top60,S\&P600}$	$R^{Exc}_{Top60EW,S\&P600}$	$R^{Exc}_{Top60,S\&P600}$
$\widehat{PassiveFlow}_{S\&P600}$	−0.00541	−0.00540	−0.00397	−0.00392
	(−1.26)	(−1.04)	(−0.94)	(−0.75)
Constant	−0.000462	−0.00121	0.00245	0.00161
	(−0.12)	(−0.28)	(0.67)	(0.39)
Observations	77	77	76	76
Controls	N	N	Y	Y
Adjusted R^2	0.025	0.019	0.197	0.164

6. Conclusion

The growth of passive investing over the past 30 years and its effects on asset prices and the real economy have attracted attention from academics and policy-makers. In this paper we show that flows into passive funds disproportionately raise the prices of the economy's largest firms. Large firms are thus less liquid than small firms, in the sense that an increase in demand proportional to firms' market capitalization causes large firms' stock prices to rise the most. The effects of passive flows that we show in our model arise even when the indices tracked by passive funds include all firms, and they can be sufficiently strong to cause the aggregate market to rise even when flows are entirely due to investors switching from active to passive. Our model implies additionally that passive flows raise the idiosyncratic return volatility of large firms more than of smaller firms. Consistent with our theory, we find that the prices and idiosyncratic volatilities of the largest firms in the S&P500 index rise the most following flows into that index.

Our theory implies that passive investing reduces primarily the financing costs of the largest firms in the economy and makes the size distribution of firms more skewed. Quantifying these effects is a natural extension of our research. A quantification exercise would also determine the contribution of the rise in passive investing to recent macroeconomic trends such as the rise in industry concentration and the decline in corporate investment. Some papers quantifying these trends emphasize heterogeneity in financing costs, which they often model through borrowing constraints. Our theory links this heterogeneity to stock-market distortions, which can be a more relevant channel for large firms.

An additional extension of our research concerns the design of indices. Passive funds in our model track capitalization-weighted indices. While such indices are the most common in practice, other types of indices, such as price-weighted or equal-weighted, also exist. It would be interesting to determine how indices should be designed to achieve welfare objectives. If the growth of passive funds reduces primarily the financing costs of the largest firms, and this leads to welfare-reducing industry concentration or capital misallocation, then should capitalization-weighting be moderated? Should upper bounds be imposed on weights, as is the case for some sovereign-bond indices? Is capitalization-weighting the best solution despite its drawbacks?

Code Availability: The replication code and data are available in the Harvard Dataverse at <https://doi.org/10.7910/DVN/YO0VL7>.

References

Alexander, L., and J. Eberly. 2018. Investment hollowing out. *IMF Economic Review* 66:5–30.

Antoniou, C., W. Li, X. Liu, A. Subrahmanyam, and C. Sun. 2022. Exchange-traded funds and real investment. *Review of Financial Studies* 36:1043–93.

Autor, D., D. Dorn, L. Katz, C. Patterson, and J. van Reenen. 2020. The fall of the labor share and the rise of superstar firms. *Quarterly Journal of Economics* 135:645–709.

Axtell, R. 2001. Zipf distribution of US firm sizes. *Science* 293:1818–20.

Basak, S., and A. Pavlova. 2013. Asset prices and institutional investors. *American Economic Review* 103:1728–58.

Ben-David, I., F. Franzoni, B. Kim, and R. Moussawi. 2022. Competition for attention in the ETF space. *Review of Financial Studies* 36:987–1042.

Ben-David, I., F. Franzoni, and R. Moussawi. 2018. Do ETFs increase volatility? *Journal of Finance* 73:2471–535.

Bhojraj, S., P. Mohanram, and S. Zhang. 2020. ETFs and information transfer across firms. *Journal of Accounting and Economics* 70:101–336.

Bond, P., and D. Garcia. 2022. The equilibrium consequences of indexing. *Review of Financial Studies* 35:3175–230.

Brennan, M. 1993. Agency and asset pricing. Working paper 1147, Anderson Graduate School of Management, University of California, Los Angeles.

Brogaard, J., M. Ringgenberg, and D. Sovich. 2018. The economic impact of index investing. *Review of Financial Studies* 32:3461–99.

Buffa, A., D. Vayanos, and P. Woolley. 2022. Asset management contracts and equilibrium prices. *Journal of Political Economy* 130:3146–201.

Buss, A., and S. Sundaresan. 2023. More risk, more information: How passive ownership can improve informational efficiency. *Review of Financial Studies* 36:4713–58.

Chabakauri, G., and O. Rytchkov. 2021. Asset pricing with index investing. *Journal of Financial Economics* 141:195–216.

Chinco, A., and M. Sammon. 2024. The passive-ownership share is double what you think it is. *Journal of Financial Economics* 157:103860–.

Coles, J., D. Heath, and M. Ringgenberg. 2022. On index investing. *Journal of Financial Economics* 145:665–83.

Covarrubias, M., G. Gutiérrez, and T. Philippon. 2019. From good to bad concentration? US industries over the past 30 years. *NBER Macroeconomics Annual* 34:1–46.

Cremers, M., and A. Petajisto. 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies* 22:3329–65.

Crouzet, N., and J. Eberly. 2023. Rents and intangible capital: A Q+ framework. *Journal of Finance* 78:1873–916.

Cuoco, D., and R. Kaniel. 2011. Equilibrium prices in the presence of delegated portfolio management. *Journal of Financial Economics* 101:264–96.

Da, Z., and S. Shive. 2018. Exchange traded funds and asset return correlations. *European Financial Management* 24:136–68.

Davies, S. 2024. Index-linked trading and stock returns. Working paper, University of Colorado.

Elsby, M., B. Hobijn, and A. Sahin. 2013. The decline of the US labor share. *Brookings Papers on Economic Activity* 44:1–63.

Fama, E., and K. French. 1992. The cross-section of expected stock returns. *Journal of Finance* 47:427–65.

Gabaix, X. 2016. Power laws in economics: An introduction. *Journal of Economic Perspectives* 30:185–206.

Gabaix, X., and R. Koijen. 2021. In search of the origins of financial fluctuations: The inelastic markets hypothesis. Working paper 28967, National Bureau of Economic Research.

Garleanu, N., and L. Pedersen. 2018. Efficiently inefficient markets for assets and asset management. *Journal of Finance* 73:1663–712.

Glosten, L., S. Nallareddy, and Y. Zou. 2020. ETF activity and informational efficiency of underlying securities. *Management Science* 67:22–47.

Grossman, S. 1976. On the efficiency of competitive stock markets where trades have diverse information. *Journal of Finance* 31:573–85.

Grossman, S., and J. Stiglitz. 1980. On the impossibility of informationnaly efficient markets. *American Economic Review* 70:393–408.

Grullon, G., Y. Larkin, and R. Michaely. 2019. Are us industries becoming more concentrated? *Review of Finance* 23:697–743.

Gutiérrez, G., and T. Philippon. 2017. Investmentless growth: An empirical investigation. *Brookings Papers on Economic Activity* 48:89–190.

Haddad, V., P. Huebner, and E. Loualiche. 2025. How competitive is the stock market? Theory, evidence from portfolios, and implications for the rise of passive investing. *American Economic Review* 115:975–1018.

Hall, R. 2014. Quantifying the lasting harm to the US economy from the financial crisis. *NBER Macroeconomics Annual* 29:71–128.

Harris, L., and E. Gurel. 1986. Price and volume effects associated with changes in the S&P500 list: New evidence for the existence of price pressures. *Journal of Finance* 41:815–29.

Kapur, S., and A. Timmermann. 2005. Relative performance evaluation contracts and asset market equilibrium. *Economic Journal* 115:1077–102.

Karabarbounis, L., and B. Neiman. 2014. The global decline of the labor share. *Quarterly Journal of Economics* 129:61–103.

Koijen, R., R. Richmond, and M. Yogo. 2024. Which investors matter for equity valuations and expected returns? *Review of Economic Studies* 91:2387–424.

Pastor, L., and R. Stambaugh. 2012. On the size of the active management industry. *Journal of Political Economy* 120:740–81.

Petajisto, A. 2013. Active share and mutual fund performance. *Financial Analysts Journal* 69:73–93.

Shleifer, A. 1986. Do demand curves for stocks slope down? *Journal of Finance* 41:579–90.

Stambaugh, R. 2014. Presidential address: Investment noise and trends. *Journal of Finance* 69:1415–53.

Subrahmanyam, A. 1991. A theory of trading in stock index futures. *Review of Financial Studies* 4:17–51.

Vayanos, D., and P. Woolley. 2013. An institutional theory of momentum and reversal. *Review of Financial Studies* 26:1087–145.

Vuolteenaho, T.. 2002. What drives firm-level stock returns?. *Journal of Finance* 57:233–64.