Passive Ownership and Corporate Investment: A Matching Perspective

Murray Z. Frank and Vidhan K. Goyal*

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Abstract

We develop a matching model in which ultimate investors, fund managers, and firms endogenously sort into optimal ownership structures. Differences in corporate investment sensitivities emerge as efficient outcomes. Using input-output demand shocks to introduce exogenous variation in opportunities, we find that firms with higher passive ownership have lower investment-Q sensitivity. Active owners are drawn to high-monitoring firms where governance costs are justified, while stable firms attract low-cost passive capital. Cross-sectional tests show the strongest effects in ownership mismatches, such as when a firm is added to an index. We show these effects vary systematically with firm characteristics in ways consistent with efficient investor-firm matching rather than uniform governance constraints. Many features of observed ownership and investment make sense from an efficient investor-firm matching perspective.

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*Frank is from the University of Minnesota; e-mail: murra280@umn.edu. Goyal is from HKUST and ABFER; e-mail: goyal@ust.hk. We have no financial relationships, funding, or other potential conflicts of interest that apply to the research in this paper.

1 Introduction

The dramatic rise of passive investing over recent decades marks one of the most significant structural shifts in modern financial markets since World War II. Figure 1 shows that passive ownership grew steadily from about 3% of the value-weighted stock market in 2000 to about 14% in 2021.[1] Capital has steadily migrated from active to passive strategies. Conventional wisdom stresses that indexing benefits investors through lower fees and broad diversification (French, 2008; Malkiel, 2019). However, the impact on corporate investment and capital allocation efficiency remains poorly understood. Passive ownership is typically associated with cheaper, more stable capital, but may also weaken governance due to limited monitoring incentives (Heath et al., 2022), raising concerns about distorted investment decisions. What are the real consequences of firms increasingly being owned by passive investors? If passive investors and index funds offer limited oversight, does their growing influence lead to suboptimal corporate policies?

— Figure 1 about here —

This paper develops and tests a model in which ownership structure is the outcome of a matching process between firms and investors. The idea is that some firms benefit from active oversight, while others primarily value low-cost, patient capital. In equilibrium, firms with high monitoring needs optimally attract active investors, whereas more stable firms with low governance demands match with passive investors. As a result, observed ownership patterns reflect endogenous investor sorting, rather than one-size-fits-all governance effects.

We formalize this intuition in a simple model where firms choose investment subject to adjustment costs that increase with passive ownership. The model produces four main predictions. First, investment-Q sensitivity declines as passive ownership increases. Second, this effect is stronger for firms with greater monitoring needs. Third, firms with greater passive ownership react to shocks more slowly. Fourth, mechanical changes in ownership, such as those triggered by index inclusion, can create mismatches that reduce investment responsiveness. This is particularly true for high-monitoring firms. These predictions are distinct from alternative explanations that view passive ownership as uniformly harmful or merely liquidity-enhancing for traders.

[1]The trend has continued beyond the time period for which we currently have the data. According to Goldman Sachs Weekly update (November 1, 2024) "During the past decade, passive equity mutual funds and ETFs have seen $2.8 trillion of inflows compared with $3.0 trillion of cumulative outflows from actively-managed funds. Alongside passive equity inflows, the share of passive ownership for the typical S&P 500 firm has also increased, rising from 18% two decades ago to 26% today." https://www.gspublishing.com/content/research/en/reports/2024/11/01/e03d5b95-7f97-45dd-967f-891c3bf12198.pdf.

We test these predictions using panel data on publicly traded U.S. firms from 2000 to 2021. We employ a two-stage empirical strategy. In the first stage, we estimate baseline investment regressions to examine how passive ownership affects the sensitivity of investment to growth opportunities (proxied by Tobin's Q), controlling for firm and year fixed effects. We complement this with industry-level demand shocks derived from input-output tables (Acemoglu et al., 2012), providing exogenous variation in Q. The results show that higher passive ownership is associated with significantly weaker investment-Q sensitivity. On its own, this suggests that passive owners make firms less responsive to growth opportunities.

In the second stage, we examine heterogeneity by interacting passive ownership with firm characteristics related to monitoring value. The effect is concentrated among firms poorly matched with passive capital, specifically those with high R&D, elevated volatility, and significant growth options. These mismatched firms show sharp declines in investment-Q sensitivity following exogenous increases in passive ownership, consistent with the predictions of our matching framework.

The magnitudes are economically meaningful. Based on our estimates, we can roughly calculate the costs of this mismatch. A high R&D firm that is exogenously shifted into a high-passive-ownership index reduces its annual investment. A one-standard-deviation increase in passive ownership leads to a $12.1 million decline in investment for a median-sized firm at the 90th percentile of Tobin's Q. The size of the effect varies substantially by firm size. For a firm at the 90th percentile of Tobin's Q, this represents approximately 1.9% of the median firm's capital stock. Thus, when high-growth firms are mismatched with passive capital, there are real economic consequences.

Overall, our paper makes both theoretical and empirical contributions. On the theoretical side, we develop a model of ownership and investment that yields four testable predictions. (i) Passive ownership reduces investment-Q sensitivity by increasing effective adjustment frictions. (ii) The effect is stronger in firms with high monitoring needs or governance complexity. (iii) Exogenous increases in passive ownership, such as index inclusions, reduce responsiveness most in firms reliant on active monitoring. (iv) Passive ownership increases persistence in investment dynamics by slowing adjustment to target capital.

Empirically, we test these predictions using data from Compustat and institutional ownership records. We document that investment-Q sensitivity declines with passive ownership, particularly in firms with high monitoring needs, that index additions generate mismatches consistent

with the model, and that passive ownership increases persistence in investment. Together, these results demonstrate that ownership composition systematically affects investment, reconciling competing views of passive investors as either neutral or detrimental.

Our paper is related to several strands of literature. First, we extend recent research on passive ownership and corporate behavior. Appel et al. (2016) document reduced investment sensitivity following Russell index inclusion, interpreting this as a governance constraint. We offer an alternative efficiency-based interpretation. Similarly, Heath et al. (2022) and Schmidt and Fahlenbrach (2017) document negative effects of passive ownership on various corporate policies, but do not consider whether these effects vary systematically with firm characteristics in ways consistent with efficient matching of investors to firms. Jiang et al. (2024) show that passive flows disproportionately elevate mega-firm valuations, potentially amplifying market concentration. Lewellen and Lowry (2021) examine how different types of institutional investors affect firm behavior. They focus on active institutions rather than the active-passive distinction central to our analysis.

There is recent work studying the implications of the growth of passive investing within the financial markets per se. Goyal et al. (2024) find that passive bond ownership reduces lending activity, easing short-sale constraints but altering capital costs. Brightman and Harvey (2025) warn of systemic risks from passive dominance, including reduced diversification and heightened comovement. These are not focuing on changes in firm decisions that we study.

Second, our empirical strategy builds on the corporate investment literature's use of external instruments to identify causal effects. Our demand shock approach follows Acemoglu et al. (2012) in exploiting input-output linkages to generate exogenous variation in investment opportunities. This complements traditional Q-theory approaches (Abel and Eberly, 1994; Bond and Van Reenen, 2007) by providing identification that does not rely on potentially endogenous market valuations. Our inclusion of intangible capital follows Peters and Taylor (2017). This helps ensure that our investment measures better reflect the scope of modern corporate investment. This adjustment is particularly important given the concentration of passive ownership among technology and R&D-intensive firms. Lee et al. (2021) interprets the declining importance of Tobin's Q as evidence of agency problems, mispricing, and hence distortions. We show instead that changing matches between passive investors and firms can instead reflect an efficient allocation of investor capital.

Third, our model uses established matching methods (Che et al., 2024), and it has conceptual parallels to Berk and Green (2004). Both emphasize efficient outcomes in the fund industry

as an equilibrium. In their paper, investor flows to skilled active managers generate decreasing returns to scale. They use that to explain non-persistent performance as equilibrium rather than failure. In our model, endogenous pairings of investors, funds, and firms produce varying investment sensitivities as value-maximizing specialization rather than as governance distortions from passive ownership.

Fourth, our model connects to the broader corporate governance literature on optimal monitoring arrangements. Shleifer and Vishny (1997) emphasize that effective governance requires matching investor capabilities with firm needs. Edmans (2014) shows how different governance mechanisms create value through distinct channels. Our contribution is to formalize this process in the context of passive versus active ownership. We show that mechanical allocation rules can disrupt efficient governance arrangements. Our perspective complements recent work on governance specialization by different types of institutional investors such as (McCahery et al., 2016; Dimson et al., 2015).

Our focus on passive ownership also complements recent research on common ownership. Due to growing passive ownership the same institutional investors hold stakes in competing firms within an industry (Azar et al., 2018; Gilje et al., 2020; Backus et al., 2021). Common ownership studies examine how overlapping shareholdings affect product market competition. We analyze instead how the passive nature of ownership influences individual firm investment decisions through governance channels. We do that by providing an explicitly efficiency-based interpretation of observed investment patterns; instead of governance constraint (Appel et al., 2016), or a monopoly power distortion (Azar et al., 2018). Our contribution is to show that these effects ought to vary systematically with firm characteristics in ways consistent with efficient matching. They are not just uniform market failures.

The rest of the paper proceeds as follows. Section 2 develops our theoretical model of firm-investor matching and derives testable predictions. Section 3 describes the data and variables. Section 4 outlines our empirical methodology, highlighting how our identification strategies address specific concerns about endogeneity. Section 5 presents main results, including baseline investment regressions and demand shock evidence. Section 6 covers robustness checks and alternative explanations. Section 7 uses the estimates to calculate the economic magnitudes of the effects we document. Section 8 concludes with policy implications and directions for future research.

2 Theory

We develop a simple matching model in which heterogeneous firms and heterogeneous capital providers endogenously sort into ownership structures. The model delivers sharp testable predictions linking passive ownership to corporate investment. We present the economic environment and the firm's problem, then state the main propositions. The formal setup is in Appendix A, and the proofs are in Appendix B.

2.1 Economic Environment

Each firm i is characterized by type $\theta_i = (\sigma_i, \kappa_i, \mu_i)$, where σ_i is business volatility, κ_i is governance complexity, and μ_i is the incremental value created by active monitoring.

There are three types of fund managers. (i) *Active managers* (A) select portfolios endogenously and provide monitoring at cost f_A, improving outcomes for firms with high μ_i. (ii) *Passive managers* (P) hold diversified portfolios with no monitoring, charging low fees f_P. (iii) *Index managers* (I) are constrained to hold firms in fixed index weights w_i^{index}, regardless of firm characteristics. They also have very low fees.

Ultimate investors allocate wealth across fund managers according to their preferences for fees and governance. In equilibrium, firms and fund managers are paired to maximize total surplus. Appendix A formalizes the matching technology.

2.2 Firm Investment Problem

Firm i chooses investment I_i given Tobin's Q (q_i) and its ownership structure. Let α_i denote the equilibrium share of passive ownership. Investment is subject to adjustment costs that increase with α_i. This is a particularly simple method to model the reduced governance pressure on firms that are less closely monitored.

$$\max_{I_i} \quad q_i I_i - \frac{1}{2}\left(\omega_0 + \gamma\alpha_i\right)\left(\frac{I_i}{K_i}\right)^2 K_i, \tag{1}$$

where K_i is the capital stock, $\omega_0 > 0$ is the baseline adjustment cost, and $\gamma > 0$ measures the incremental cost from reduced monitoring.

The parameter γ represents the idea that passive investors have only limited monitoring incentives. Accordingly the firms with high passive ownership face less pressure to adjust their

capital stock rapidly. Some firms probably require active oversight such as those with high R&D or growth options. Passive ownership reduces the pressure on managers, as these investors are less likely to engage in value-enhancing interactions with management. Our use of γ provides a particularly simple and clear method of reflecting this idea.

The first-order condition is

$$\frac{\partial(I_i/K_i)}{\partial q_i} = \frac{1}{\omega_0 + \gamma\alpha_i}. \tag{2}$$

This shows that higher passive ownership lowers investment responsiveness to Q.

2.3 Matching and Equilibrium

The surplus from matching firm i with manager type τ is

$$S(\theta_i, \tau) = \Pi(\theta_i, \tau) - C(\theta_i, \tau) - M(\theta_i, \tau), \tag{3}$$

where Π is value creation, C is direct costs, and M is the mismatch penalty. In equilibrium, high-μ_i and high-κ_i firms optimally match with active managers, while low-volatility, low-μ_i firms match with passive managers. Index inclusion mechanically raises α_i, potentially creating mismatches.

For our equilibrium definition we use the standard concept of a competitive equilibrium in a transferable utility (TU) assignment model (Che et al., 2024). For finance applications transferable utility seems reasonable since money can change hands. A discussion of the equilibrium definition is provided in Internet Appendix IG.

2.4 Propositions

We summarize the model's main implications as propositions. Proofs are provided in Appendix B.

Proposition 1 (Investment-Q Sensitivity) *For firm i with passive ownership share α_i, the equilibrium sensitivity of investment to Tobin's Q is $\frac{\partial(I_i/K_i)}{\partial q_i} = \frac{1}{\omega_0+\gamma\alpha_i}$. This demonstrates that the investment-Q sensitivity is strictly decreasing in α_i.*

More passive ownership raises effective convexity in adjustment costs, making firms less responsive to changes in investment opportunities.

Proposition 2 (Heterogeneous Effects) *The reduction in investment-Q sensitivity due to passive ownership is larger for firms with higher monitoring value μ_i and greater governance complexity κ_i. Such firms optimally match with active managers in the absence of shocks.*

Firms that benefit most from active monitoring lose the most when forced into matches with passive investors.

Proposition 3 (Index Shocks and Mismatch) *Mechanical increases in passive ownership due to index inclusion raise α_i for affected firms. The resulting decline in investment-Q sensitivity is strongest for firms with high μ_i and κ_i. These are the firms where the mismatch with passive capital is most severe.*

Mechanical ownership shifts disrupt the optimal allocation between firms and active monitors, lowering responsiveness.

Proposition 4 (Adjustment Dynamics) *Firms with higher passive ownership exhibit slower adjustment of investment toward target levels. In dynamic specifications, the coefficient on lagged investment rises with α_i. This indicates greater persistence of investment rates.*

By raising adjustment frictions, passive ownership slows the speed at which firms converge to optimal capital.

— Figure 2 about here —

Figure 2 shows the main mechanism of the model. Panel (a) shows the surplus functions for active (A) and passive (P) manager types as a function of firm monitoring needs (μ_i). The active surplus function exhibits a positive slope, reflecting that monitoring creates increasing value as firm needs rise: $\Pi(\theta_i, A) = \bar{\pi} + \mu_i - \kappa_i^2/2$. Active matches initially generate lower surplus than passive matches due to higher monitoring costs, but this relationship reverses as μ_i increases beyond the intersection point.

The passive surplus function declines linearly with μ_i, representing the surplus $S(\theta_i, P) = \bar{\pi} - C_P - M(\theta_i, P)$. This negative slope reflects increasing mismatch costs as monitoring needs rise. Passive managers' lack of oversight becomes increasingly costly when firms require active governance, resulting in lower net surplus. The intersection point at $\mu_i = 4$ determines the threshold where firms switch from preferring passive to active ownership.

Panel (b) shows the resulting equilibrium passive ownership share (α_i) across firm types. The sigmoid relationship demonstrates smooth sorting in equilibrium. Low-monitoring-need

firms (μ_i near 0) optimally match with low-cost passive capital, exhibiting high passive ownership shares near unity. As μ_i rises toward the threshold, the transition to active ownership accelerates, creating the steepest decline around the surplus crossover point. High-monitoring firms ($\mu_i > 5$) predominantly sort into active ownership structures.

This matching equilibrium generates the model's main predictions. Higher passive ownership reduces investment-Q sensitivity (Proposition 1), with stronger effects concentrated among high-μ_i firms that are mismatched with passive capital (Proposition 2).

2.5 Alternative Explanations

Our matching framework implies that observed differences in investment-Q sensitivity reflect efficient specialization rather than uniform governance constraints. Alternative explanations yield different predictions. (i) A uniform constraint model predicts that passive ownership reduces responsiveness equally across all firms. (ii) A liquidity channel theory suggests that passive ownership enhances investment efficiency by lowering financing frictions. (iii) A selection story posits that observed correlations reflect sorting on unobservables, but no differential effects across observable firm types.

In contrast, our model predicts that ownership effects vary systematically with firm-level attributes and are amplified by mechanical reallocations, such as those triggered by index inclusion. These sharp, differentiating predictions guide our empirical tests in Section 5.

3 Data and Measurement

This section details our data construction and key variable definitions. We compile a comprehensive dataset linking corporate investment decisions to ownership structures and industry demand conditions. Our empirical strategy requires careful measurement of passive ownership, investment opportunities, and exogenous demand variation to identify the causal effects of ownership structure on corporate investment behavior.

3.1 Sample Construction

Our sample comprises publicly traded U.S. firms from 2000 to 2021, using data from Compustat, CRSP, and Thomson Reuters institutional holdings databases. Starting with all firm-year observations in Compustat, we apply several screens to ensure data quality and economic relevance.

We exclude financial firms (SIC 6000-6999), regulated utilities (SIC 4900-4949), and public administration and international affairs (SIC 9000+) due to their distinct regulatory or economic environments affecting investment. Following Peters and Taylor (2017) and Andrei et al. (2019), we retain firms with positive book values of assets and sales, and gross property, plant, and equipment (PPE) of at least $5 million, thereby excluding very small firms with unreliable investment data or atypical ownership patterns.

All ratio variables are winsorized at the 1% level to limit the influence of extreme outliers. The final sample comprises 76,325 firm-year observations, representing 8,547 unique firms over a 22-year period. This period captures substantial variation in both ownership structures and investment patterns, coinciding with the dramatic rise of passive investing. It went from under 5% to over 20%. This provides the necessary variation to identify its effects on corporate decisions.

3.2 Passive Ownership Measurement

Measuring passive ownership requires distinguishing passive from active funds. Several approaches have been adopted in various studies (Chinco and Sammon, 2024; Sammon, 2025). We merge Thomson Reuters S12 mutual fund holdings with the CRSP Mutual Fund Database and classify funds as passive using two criteria. First, we identify funds flagged by CRSP with codes "B," "D," or "E," which denote index-tracking strategies with minimal active management. Second, following Appel et al. (2016), we classify funds as passive if their names contain keywords associated with index strategies (e.g., "Index," "Russell," "S&P," "Dow," "NASDAQ," and specific index numbers like "500," "1000," or "2000"), capturing index-like strategies not explicitly flagged in CRSP.

For each firm-year, passive ownership is measured as the fraction of outstanding shares held by funds meeting either criterion. Dollar holdings are converted to ownership percentages using CRSP share price and shares outstanding. Our measure correlates at over 0.85 with alternatives based solely on fund names or expense ratios, supporting its validity. Time-series patterns align with industry trends: Figure 1 shows that value-weighted passive ownership rose from about 3% in 2000 to over 14% by 2021, with a similar but smaller increase on an equal-weighted basis, reflecting the concentration of passive investing in larger firms that dominate major indices.

3.3 Investment and Firm Characteristics

We measure investment rates following Peters and Taylor (2017), incorporating intangible capital to correct for mismeasurement in traditional measures. Total investment includes (1) capital expenditures (`capx`), (2) R&D expenditures (`xrd`), and (3) organization capital, imputed as 30% of selling, general, and administrative (`xsga`) expenses net of R&D, following Eisfeldt and Papanikolaou (2014) and Peters and Taylor (2017).

Total capital stock is the sum of gross property, plant, and equipment (`ppegt`) and intangible capital following Peters and Taylor (2017) and obtained via WRDS. Intangible capital reflects accumulated R&D and a portion of SG&A, depreciated at asset-specific rates.[2] Tobin's Q is measured as firm value (market equity plus book debt minus current assets) scaled by the replacement cost of total capital, excluding liquid assets. Cash flow is measured as operating income before extraordinary items plus depreciation, with after-tax intangible investments added back to avoid double counting in both cash flow and investment.

— Table 1 about here —

Table 1 summarizes statistics for key variables. The average investment rate is 17.6%, higher than traditional estimates due to the inclusion of intangible investments. The median Tobin's Q of 0.72 suggests that most firms face relatively limited investment opportunities, consistent with the maturity of many public companies. Passive ownership averages 5.9%, with the 90th percentile reaching 15.0%, offering substantial cross-sectional variation to identify its impact on corporate behavior.

3.4 Descriptive Patterns

Table 2 summarizes investment patterns across passive ownership terciles. Firms in the lowest tercile (mean ownership 1.4%) invest an average of 18.6% of capital, with high volatility (16.0%) and low persistence (AR(1)=0.36). Their investment-Q sensitivity is highest at 0.031, a 33% decline in Q-sensitivity (0.027) relative to the lowest tercile, indicating strong responsiveness to investment opportunities. Firms in the middle tercile (5.6% ownership) exhibit similar average investment (18.5%) but lower volatility (15.3%), higher persistence (0.47), and a modestly reduced Q-sensitivity

[2] Organizational capital is calculated using the perpetual inventory method: the prior period's organizational capital (depreciated at 20%) plus 30% of current-period SG&A. See Eisfeldt and Papanikolaou (2014) and Peters and Taylor (2017) for details and justification for using SG&A as a proxy for organizational capital investment.

(0.034). The highest tercile (10.8% ownership) displays distinct patterns: lower average investment rates (15.9%), the lowest volatility (12.0%), the highest persistence (0.50). This is, a 29% decline in Q-sensitivity (0.022) relative to the lowest tercile $((0.031 - 0.022)/0.031 \approx 0.29)$.

— Figure 3 about here —

These patterns support our matching framework. Higher passive ownership is associated with more persistent, less volatile investment and reduced responsiveness to growth opportunities. This is consistent with the concept of 'slow capital' that adjusts gradually to changing conditions.

— Table 2 about here —

4 Empirical Strategy

Our goal is to estimate the causal effect of passive ownership on a firm's investment sensitivity to growth opportunities. The predictions in Section 2 directly guide our empirical strategy.

Prediction 1 implies that the interaction of Tobin's Q and passive ownership, $\alpha_i \times Q_i$, should enter the investment regressions with a negative coefficient. Prediction 2 further suggests that this negative effect is stronger for firms with characteristics that increase the value of active monitoring. Examples include high R&D intensity, elevated volatility, or complex governance structures.

We begin with a fixed-effects panel regression to estimate the relationship between passive ownership and investment sensitivity to growth opportunities.

$$\frac{I_{it}}{K_{i,t-1}} = \beta_0 + \beta_Q Q_{i,t-1} + \beta_\alpha \alpha_{it} + \beta_{\alpha Q}(\alpha_{it} \times Q_{i,t-1}) + \beta_{\text{CF}} \frac{CF_{it}}{K_{i,t-1}} + \gamma' X_{it} + \delta_i + \tau_t + \varepsilon_{it}, \quad (4)$$

where I_{it} is total investment, $K_{i,t-1}$ is beginning-of-year capital, $Q_{i,t-1}$ is Tobin's Q, α_{it} is the fraction of shares held by passive investors, CF_{it} is cash flow, X_{it} is a vector of controls, δ_i are firm fixed effects, τ_t are year fixed effects, and ε_{it} is the error term.

The coefficient of primary interest, $\beta_{\alpha Q}$, captures the effect of passive ownership on investment-Q sensitivity. According to Prediction 1, we expect $\beta_{\alpha Q} < 0$, indicating that higher passive ownership reduces the responsiveness of investment to growth opportunities.

4.1 Controlling for Industry-Level Shocks

To account for correlated shocks within industries, we include a measure of exogenous demand variation following Acemoglu et al. (2012). For each producer industry j, the demand shock is defined as:

$$\text{Shock}_{jt} = \sum_{k} w_{jk}\, g_{kt}, \tag{5}$$

where w_{jk} is the share of industry j's output sold to customer industry k, and g_{kt} is the growth in sales of industry k. This measure captures downstream demand fluctuations that are plausibly exogenous to firm i's own productivity or investment decisions.

We then estimate equation 4 both with and without Shock_{jt} and its interaction with high passive ownership, allowing us to test Prediction 2.

We identify demand shocks under the assumption that industry-level demand shocks affect firm investment solely through their impact on expected profitability, captured by Tobin's Q. That is, these shocks affect investment opportunities but do not directly impact ownership composition, financing conditions, or other unobserved investment drivers. This exclusion restriction rules out alternative channels where demand shocks simultaneously affect passive ownership or credit supply. To support this assumption, we: (i) control for time-varying industry fixed effects and aggregate trends; (ii) show that demand shocks are uncorrelated with contemporaneous changes in ownership composition; and (iii) confirm robustness by excluding industries with unusually high passive inflows. Together, these tests reduce concerns about violations of the exclusion restriction.

The exclusion restriction is important. To confirm the validity of our demand shock instrument, we test whether industry demand shocks predict subsequent changes in passive ownership. Consider Table IE of the Internet Appendix. Across specifications with varying fixed effects and controls, the coefficients on lagged shocks are economically small (ranging from 0.000 to 0.007) and statistically insignificant. This orthogonality supports the exclusion restriction.

This evidence ensures that shocks affect investment solely through growth opportunities rather than by altering ownership structures endogenously. By ruling out reverse causality, these findings strengthen our causal interpretation of the demand shock results in Section 5. This bolsters the use of exogenous variation to identify ownership effects as in Proposition 3. Industry demand shocks do not predict subsequent changes in passive ownership.

4.2 Heterogeneity Tests

To test Prediction 2 directly, we augment 4 with triple interactions.

$$\frac{I_{it}}{K_{i,t-1}} = \cdots + \beta_{\alpha QZ}(\alpha_{it} \times Q_{i,t-1} \times Z_{it}) + \ldots, \tag{6}$$

where Z_{it} captures firm characteristics such as R&D intensity, volatility, or governance complexity. A significantly negative $\beta_{\alpha QZ}$ indicates that the dampening effect of passive ownership on investment-Q sensitivity is concentrated among firms with a high value of active monitoring.

4.3 Dynamic Specifications

To assess whether passive ownership influences the speed of investment adjustment, we estimate dynamic panel models of the form:

$$\frac{I_{it}}{K_{i,t-1}} = \lambda \frac{I_{i,t-1}}{K_{i,t-2}} + \beta_Q Q_{i,t-1} + \beta_{\alpha Q}(\alpha_{it} \times Q_{i,t-1}) + \ldots \tag{7}$$

Differences in the estimated adjusted coefficient λ across levels of passive ownership provide evidence on whether passive capital is associated with slower investment adjustment, complementing the Q-sensitivity results from the baseline regression.

This empirical framework maps directly onto the theoretical predictions:

- Prediction 1: $\beta_{\alpha Q} < 0$ in 4, indicating that passive ownership reduces investment-Q sensitivity.
- Prediction 2: $\beta_{\alpha QZ} < 0$ for high monitoring-value firms, such as those with high R&D intensity, volatility, or governance complexity.

This structure ensures that each empirical test corresponds to a specific theoretical prediction, making the link between theory and evidence transparent.

5 Evidence

This section presents empirical evidence on the relationship between passive ownership and corporate investment. Using multiple identification strategies, we find consistent results that support

a matching framework: firms with higher passive ownership exhibit lower investment sensitivity to growth opportunities, consistent with efficient sorting between investors and firms.

We begin by estimating an investment equation to test whether passive ownership dampens the responsiveness of investment to Tobin's Q. Our baseline specification is a panel regression with firm and year fixed effects:

$$\frac{I_{it}}{K_{it-1}} = \alpha + \beta_1 Q_{it-1} + \beta_2 \text{OwnPassive}_{it} + \beta_3 (\text{OwnPassive}_{it} \times Q_{it-1}) + \beta_4 \frac{CF_{it}}{K_{it-1}} + \gamma X_{it} + \tau_t + \delta_i + \varepsilon_{it}. \tag{8}$$

The coefficient of interest is β_3, which we expect to be negative under our framework.

— Table 3 about here —

Table 3 presents the estimation results. The interaction term coefficient, β_3, is negative and statistically significant across all specifications. In our preferred specification (Column 4), which includes the full set of controls, the estimate for β_3 is -0.152 with a standard error of 0.011. This implies that a one-standard-deviation increase in passive ownership reduces investment-Q sensitivity by 23% relative to the sample mean $(0.06 \times 0.152/0.040 \approx 0.228)$. The direct effect of passive ownership, β_2, is positive (0.123), indicating that firms with higher passive ownership tend to invest more on average. This is consistent with the observation that larger firms, which tend to attract more passive ownership, also exhibit higher investment rates. However, this estimate should not be interpreted causal.

The economic magnitude of the effect is large. For a median-sized firm at the 90th percentile of Tobin's Q, a one-standard-deviation increase in passive ownership leads to a $12.1 million decline in investment using facts from Table 3 Column 4 and Table 1. This represents approximately 2.8% of the median firm's capital stock $(-12.1/439 \approx 2.8\%)$.

These impacts are clearly statistically significant and of reasonable magnitudes. For most firms, the impact ranges are fairly modest relative to total investment budgets, typically ranging from about $\$0.4$ million to $\$8.6$ million. However, for large firms with high growth opportunities, the effects can be substantially larger. These firms are also the most likely to be newly added to major indices, making the implications of passive ownership particularly relevant. Firm size and firm growth as measured by Tobin's Q are central to the magnitudes. For more details see Section 7.

5.1 Cross-Section Heterogeneity

We next examine whether the sensitivity of investment to Tobin's *Q* varies across firms with differing match quality between ownership structures and firm characteristics. Specifically, we test whether passive ownership affects investment-*Q* sensitivity differently for subsamples partitioned by firm characteristics that proxy for monitoring needs.

To do so, we sort firms by return volatility, income volatility, and R&D intensity, and estimate whether the relationship between investment and Tobin's *Q* differs across terciles of passive ownership. We augment our baseline specification (Equation 4) by including interactions of $Q_{i,t-1}$ with binary indicators for firms in the top ($\texttt{DPassive}^{Top}$) and bottom ($\texttt{DPassive}^{Bottom}$) terciles of passive ownership:

$$\begin{aligned}\frac{I_{it}}{K_{i,t-1}} = \beta_0 + \beta_Q Q_{i,t-1} + \beta_{\alpha^{Top}Q} DPassive^{Top} \times Q_{i,t-1} \\ + \beta_{\alpha^{Bottom}Q} DPassive^{Bottom} \times Q_{i,t-1} + \beta_{\alpha^{Top}} DPassive^{Top} \\ + \beta_{\alpha^{Bottom}} DPassive^{Bottom} + \beta_{\text{CF}} \frac{CF_{it}}{K_{i,t-1}} + \delta_i + \tau_t + \varepsilon_{it}.\end{aligned} \tag{9}$$

Table 4 presents the results. Columns (1) and (2), which focus on return volatility, show that high passive ownership strengthens investment-Q sensitivity for firms with low volatility, while low passive ownership (i.e., more active ownership) enhances sensitivity for high-volatility firms. The coefficient on the interaction $DPassive^{Bottom} \times Q_{i,t-1}$ is positive and statistically significant at the 1% level.

These findings are consistent with the prediction that passive ownership is more effective when monitoring needs are low, while active ownership is more beneficial when monitoring needs are high. This supports the matching model's implications that ownership structures are endogenously sorted to firm characteristics (Proposition 2).

A similar pattern emerges for income volatility. In the high-volatility subsample, low passive ownership significantly increases investment-Q sensitivity (significant at the 5% level), again consistent with the idea that active monitoring is more valuable when firm performance is uncertain.

The R&D intensity results further reinforce this view. In the high-R&D group, the interaction between high passive ownership and *Q* is negative (-0.003, p <0.10), as predicted. In contrast, the interaction with low passive ownership is strongly positive (0.009, p <0.01), suggesting that R&D

intensive firms (those with high governance complexity) benefit more from active ownership.

These patterns complement the baseline estimates in Table 3, where passive ownership uniformly dampens Q-sensitivity. They also reinforce the demand shock evidence in Table 6, which shows reduced responsiveness to exogenous opportunities among high passive ownership firms.

Overall, the results support the matching framework's prediction that investment-Q sensitivity varies systematically with ownership-firm match quality, particularly in settings with high monitoring needs. While Table 4 does not directly test Proposition 3, the stronger effects in high-monitoring-need firms are consistent with the idea that mechanical ownership changes can amplify mismatches. This complements Proposition 1 and Proposition 4, which predict reduced responsiveness and slower adjustment in high passive ownership firms.

5.2 Industry Demand Shock Evidence

Investment regressions traditionally rely on Tobin's *Q*, often paying limited attention to endogeneity concerns (Bond and Van Reenen, 2007). Recent studies, however, highlight the importance of addressing *Q*'s endogeneity. To mitigate these concerns, we use exogenous variation in investment opportunities, leveraging industry-level demand shocks derived from input-output linkages. This approach avoids reliance on potentially endogenous firm-level measures such as Tobin's Q.

Following Acemoglu et al. (2012), we construct demand shocks as the weighted average growth rate of downstream customer industries. The weights reflect the share of each producer industry's output sold to specific customer sectors. For industry j at time t, the shock is defined as:

$$\text{Shock}_{jt} = \sum_{k \neq j} \omega_{jk} \times \Delta\text{Sales}_{kt}. \tag{10}$$

Here, ω_{jk} denotes the input-output weight for industry j's sales to customer industry k, and ΔSales_{kt} is the growth rate of industry k. We exclude intra-industry flows to isolate external demand variation that is plausibly exogenous to firm decisions.

Column (1) of Table 6 shows that demand shocks significantly predict investment, with a coefficient of 0.061 (standard error 0.011). This confirms that our shock measure captures meaningful variation in investment opportunities. A one-standard-deviation shock (0.12) increases investment rates by approximately 0.73 percentage points, indicating economically significant effects.

Columns (2) and (3) estimate the model separately for firms in the bottom and top terciles

of passive ownership. Firms in the bottom tercile show a shock sensitivity of 0.090, while those in the top tercile respond with a coefficient of 0.037. These findings align with earlier results using regression on Q, confirming that firms with higher passive ownership are less responsive to investment opportunities. Column (4) includes an interaction between the demand shock and a dummy for top-tercile passive ownership. The interaction coefficient is -0.034 (SE = 0.019), statistically significant at the 5% level, indicating that firms in the top tercile respond about 48% less to demand shocks than the rest of the sample.

Column (5) tests robustness by replacing year fixed effects with industry-year fixed effects, addressing concerns that unobservable, time-varying industry factors may correlate differently with demand shocks across firms with varying levels of passive ownership. The results remain robust, confirming that our findings are not driven by omitted industry-specific trends. Column (6) further strengthens the analysis by excluding industries with high passive investor flows. In this restricted sample, the sensitivity of investment to demand shocks is even stronger among firms with low passive ownership, reinforcing the main results.

We further validate the exclusion restriction underlying our instrument by testing whether demand shocks directly influence ownership composition. Internet Appendix Table IE regresses changes in passive ownership on lagged industry demand shocks. The coefficients are economically small (ranging from -0.001 to 0.009) and statistically insignificant across all specifications, supporting the orthogonality of demand shocks to ownership changes.

These results provide causal support for our model's core prediction, using an identification strategy that addresses endogeneity concerns inherent in Q-based tests. By leveraging upstream supply chain linkages, the demand shock approach generates variation in investment opportunities that is orthogonal to firm-specific factors potentially correlated with ownership structure. The reduced responsiveness among high passive ownership firms aligns with our theoretical framework and strengthens the baseline Q-sensitivity findings through an independent, exogenous source of variation.

5.3 Investment Dynamic Responses and Endogeneity

To account for the dynamic nature of investment and address concerns about the endogeneity of regressors, we re-estimate our baseline model using the system generalized method of moments (GMM) estimator developed by Arellano and Bond (1991) and Blundell and Bond (1998). This method is well-suited for panels with a short time dimension and a large cross-section, as

in our sample. The GMM estimator controls for unobserved firm-specific effects and potential endogeneity by using lagged levels and differences of the regressors as instruments.

Table 5 provides evidence consistent with the theoretical prediction that passive ownership affects investment dynamics by altering adjustment frictions. Specifically, the results show that firms with higher passive ownership exhibit greater persistence in investment rates, as predicted by Proposition 4. The matching framework predicts that passive ownership increases effective adjustment costs, which directly translates into higher persistence in the autoregressive specification. It implies that passive investors who are more stable and less costly, lead firms to prioritize cost minimization over rapid adjustment, resulting in smoother convergence to target investment levels.

The coefficient on lagged investment increases monotonically across passive ownership terciles. It rises from 0.246 in the low tercile to 0.321 in the high tercile. This indicates that firms with greater passive ownership adjust more gradually to their optimal investment levels. All coefficients are statistically significant at the 1% level.

The results complement the baseline findings in Table 3, which show that passive ownership reduces the contemporaneous sensitivity of investment to Tobin's Q. Table 5 reveals that this reduced responsiveness reflects a systematic preference for smoother adjustment paths, not an inability to reach appropriate long-run investment targets. This distinction is crucial for interpreting the implications of the matching process.

Importantly, investment responsiveness to Q remains positive and significant across all ownership terciles, ranging from 0.027 in the bottom tercile to 0.016 in the top tercile. The persistence of Q-sensitivity, even among high passive ownership firms, supports the efficiency interpretation of the matching framework. Firms with different ownership structures reach similar long-run responses to investment opportunities, but follow distinct adjustment trajectories shaped by their optimal governance arrangements.

These findings distinguish our matching framework from alternative explanations that imply permanent impairments in investment efficiency. Instead, the evidence suggests that while passive ownership alters the timing of investment adjustment, it does not prevent firms from ultimately reaching appropriate capital allocation decisions. This temporal smoothing may represent a reasonable trade-off for firms that benefit from stable, low-cost capital relationships.

6 Robustness

This section examines the robustness of our main findings to alternative measurement approaches, sample definitions, and identification assumptions. We conduct extensive sensitivity analyses to ensure our results are not driven by specific methodological choices or spurious correlations. The evidence consistently supports our matching framework across different specifications, time periods, and variable definitions.

Alternative Passive Ownership Measures Our baseline measure of passive ownership combines two classification methods: the CRSP index fund flag and keyword-based identification, following Appel et al. (2016). This hybrid approach balances coverage and precision. However, alternative definitions are common in the literature (Bushee, 2001; Appel et al., 2016; Chinco and Sammon, 2024). We therefore test the robustness of baseline results using alternative measures of passive ownership in Internet Appendix Table IB. For comparison, Column (1) we report the baseline results from Table 3, Column (4) : (1) ETF holdings, which broadly reflect passive strategies, and (2) quasi-indexer ownership, following Bushee (2001).

The negative interaction between passive ownership and Tobin's Q remains statistically significant across the alternative measures. The ETF-only specification has the strongest effect (-0.155). The quasi-indexer measure produces a smaller but still significant coefficient (-0.029). Alternative passive ownership definitions show that our main results do not depend on specific classification schemes for identifying passive investors. The magnitudes do vary. The consistency of the signs across methodologically distinct approaches to defining passive ownership is reassuring.

Alternative Time Sub-Periods We next examine whether the relationship between passive ownership and investment sensitivity has changed over time as passive investing has expanded. To do so, we estimate the baseline investment regression separately for four sub-periods: 2000-2005, 2006-2010, 2011-2015, and 2016-2021. The results, reported in Internet Appendix Table ID, show that the negative interaction between passive ownership and Tobin's Q remains statistically significant in all sub-periods, with coefficients ranging from -0.152 to -0.069.

The effect appears to weaken somewhat in the most recent decade, potentially reflecting market adaptation or learning effects as passive investing becomes more widespread. Importantly, the consistency of the results across time provides strong evidence against the possibility

that our findings are driven by specific economic episodes, such as the dot-com bust or the global financial crisis. These results support Proposition 1, confirming that higher passive ownership is associated with reduced investment-Q sensitivity throughout the sample period.

7 Economic Magnitudes

This section quantifies the economic significance of passive ownership effects on corporate investment, translating regression estimates into dollar impact for representative firms and assessing broader implications for capital allocation efficiency. Table 7 presents these calculations using estimates from Table 3, Column 4. We consider two firm sizes from Table 1: the median capital stock ($439 million) and the 90th percentile ($6.63 billion). Effects are evaluated across different levels of investment opportunities, using Tobin's Q values from the sample distribution.

Panel A focuses on a median-sized firm. With median capital stock and median growth opportunities (Q = 0.72), a one-standard-deviation increase in passive ownership (6 percentage points) leads to a net investment increase of $1.1 million that is driven by a direct effect of $3.5 million, partially offset by a $2.4 million negative interaction effect. For the same firm with high growth (90th percentile Q=2.95), the interaction effect dominates, resulting in a net investment decline of $6.1 million.

Panel B examines a large firm at the 90th percentile of capital stock. The effects scale with size: for a firm at the 90th percentile of both size and growth, a one-standard-deviation increase in passive ownership reduces annual investment by $134.7 million. This is large in absolute terms, but this represents about 2.0% of the firm's capital stock.

Panel C evaluates responsiveness to industry demand shocks using data from Table 6. A 75th percentile positive shock increases investment by $10.9 million for firms with low passive ownership, but only $7.3 million for high passive ownership firms. The $3.6 million gap quantifies the reduced responsiveness to exogenous investment opportunities documented previously.

Overall, these calculations show that while passive ownership effects are statistically robust, they are economically modest for most firms. For a typical firm, a one-standard-deviation change in passive ownership leads to an investment adjustment of $1.6-8.9 million annually. The effects become more substantial for large firms with strong growth prospects. These are precisely the firms most likely to experience significant ownership shifts due to index inclusion.

The modest magnitude of effects for typical firms supports the efficiency interpretation

that is fundamental to our matching framework. If passive ownership imposed uniform governance constraints, we would expect widespread investment distortions. Instead, the concentration of effects among mismatched firms suggests that the observed patterns reflect departures from optimal sorting rather than systematic market failures.

8 Conclusion

We present a framework linking the rise of passive ownership to corporate investment behavior, grounded in a model of efficient matching between firms and investors. The central empirical finding is that high passive ownership reduces investment–Tobin's Q sensitivity, with particularly strong effects among firms that stand to benefit most from active monitoring.

Our empirical analysis yields three main results. First, firms with greater passive ownership exhibit weaker responsiveness of investment to Tobin's Q. Second, the effect is concentrated in firms with high governance complexity or high monitoring value. Third, index reconstitutions that mechanically increase passive ownership reduce Q-sensitivity. This is particularly true for firms that optimally rely on active investors. These patterns confirm the model's predictions and quantify the costs of mismatches between firm needs and investor types.

Our perspective offers a unifying view of ownership, moving beyond the dichotomy of passive investors as either ineffective monitors or neutral liquidity providers. Instead, we show that ownership composition reflects endogenous sorting, which explains systematic differences in investment responses and the distortions caused by exogenous shifts in investor composition, such as index inclusion. For the median firm, these shifts impose limited costs relative to firm size.

The results have policy implications. While the overall rise in passive ownership appears to reflect efficient matching, mechanical shifts in ownership due to index rules can impose real costs. This is particularly true for firms with high monitoring needs. Future research could extend this framework to other corporate policies, including innovation, payout decisions, and labor investment. More broadly, our analysis illustrates how time-varying ownership composition can alter corporate dynamics in ways that transcend traditional debates on governance and market efficiency.

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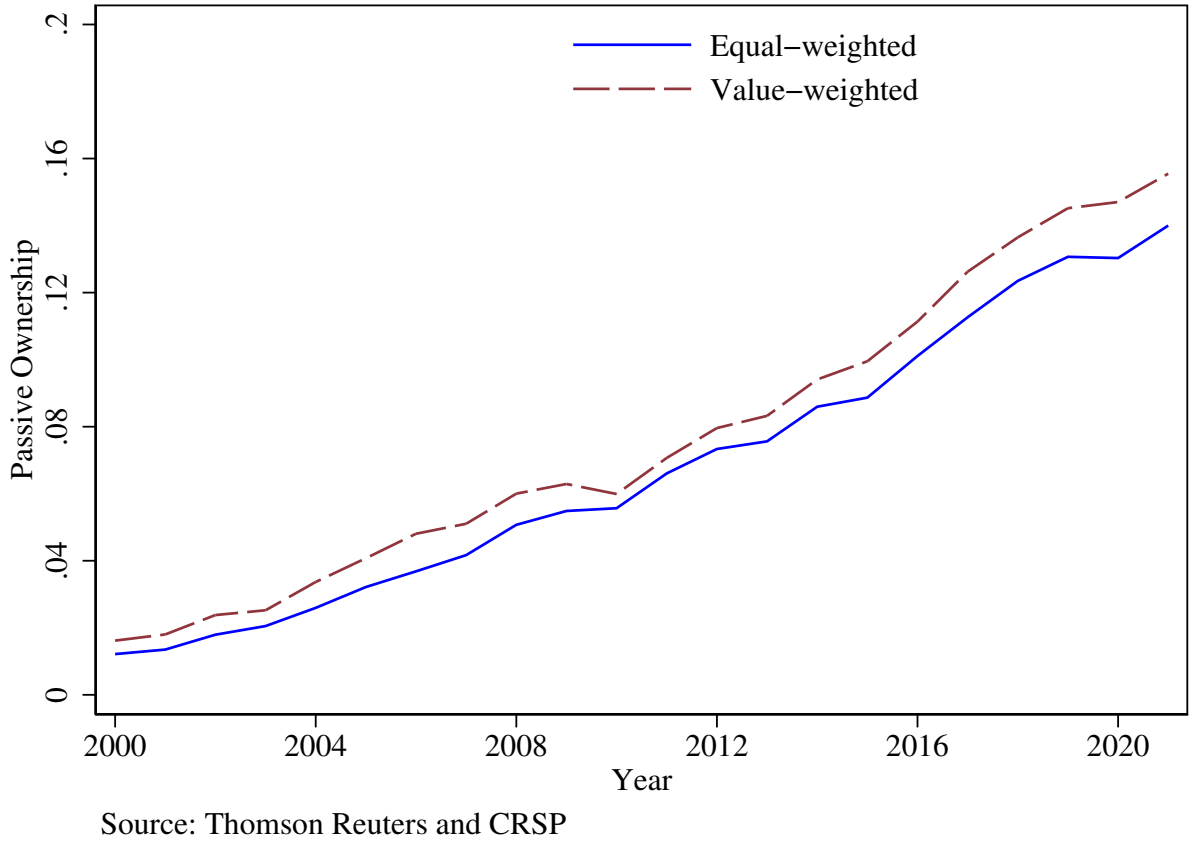
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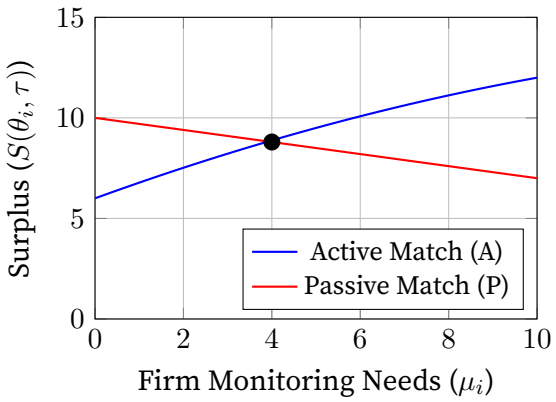
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Figure 1: Trends in Passive Ownership, 2000-2021

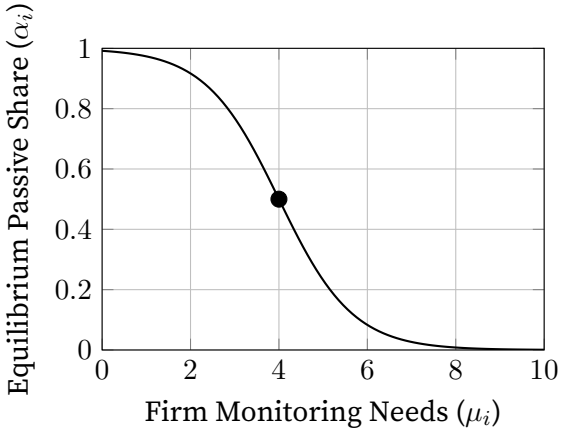


Notes. This figure plots the average percentage of shares held by passive institutional investors from 2000 to 2021. The solid line represents the equal-weighted average across all firms in our sample. The dashed line represents the value-weighted average.

Figure 2: Model Illustration: Equilibrium Matching and Surplus Functions

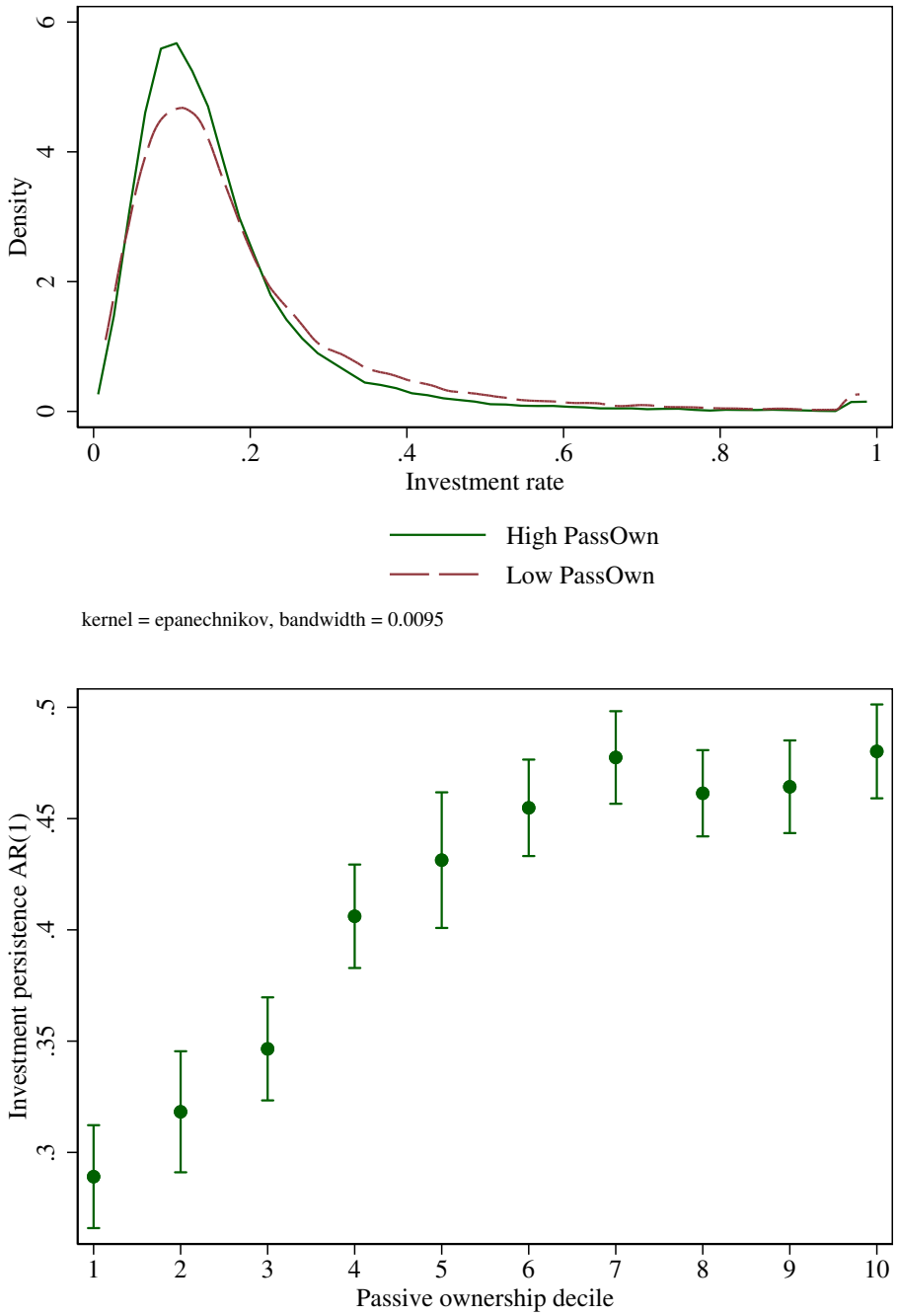


(a) Surplus Functions by Manager Type



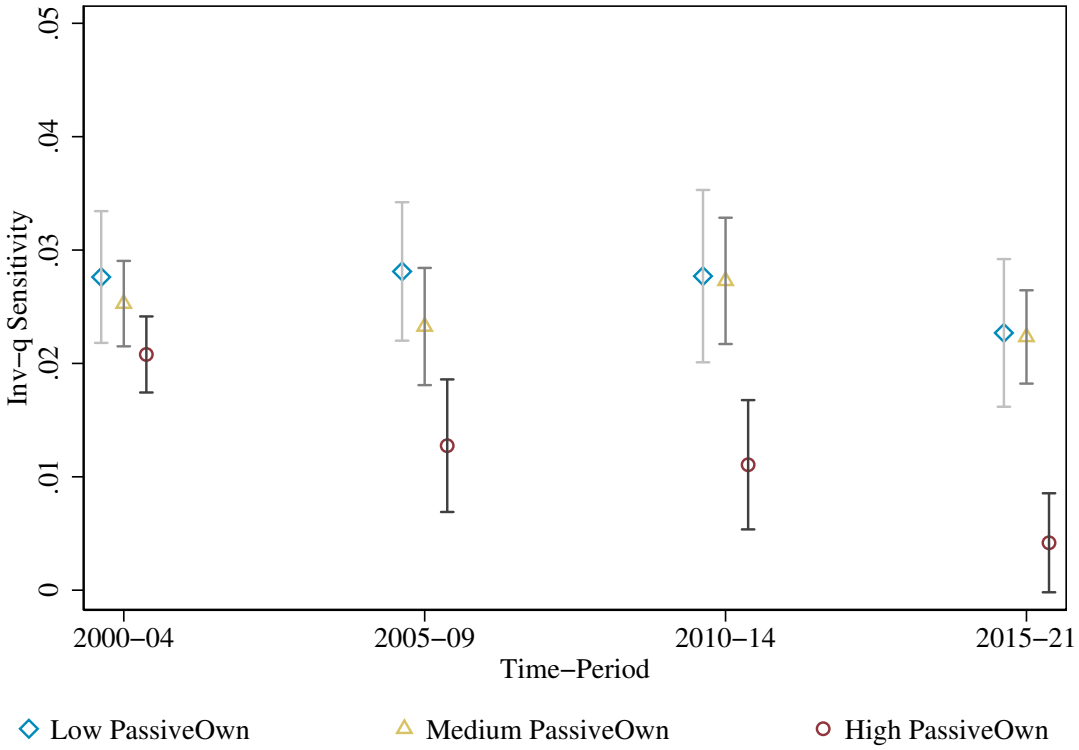
(b) Equilibrium Passive Ownership by Firm Type

Figure 3: Investment Persistence



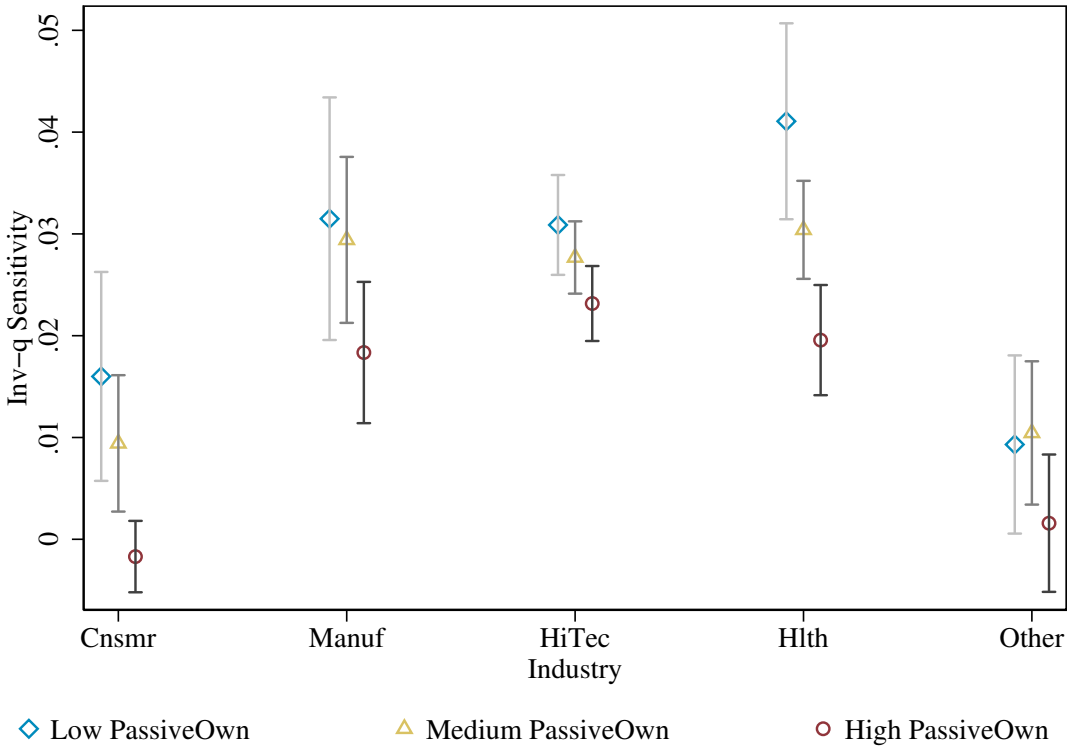
Notes. The upper panel plots kernel density estimates of investment rate distributions for firms with high passive ownership (above median, solid line) and low passive ownership (below median, dashed line). The lower panel plots the average first-order autocorrelation of investment rates across passive ownership deciles. Firms are sorted into deciles each year based on their percentage of passive ownership.

Figure 4: Evolution of Investment-Q Sensitivity Over Time



Notes. This figure plots the estimated investment-q sensitivity for passive ownership tercile by various sub-periods.

Figure 5: Passive Ownership on Investment-Q Sensitivity: Direct Effects by Industry



Notes. This figure plots the estimated effect of passive ownership on investment-q sensitivity for Fama-French industries.

Table 1:
Summary Statistics

This table reports summary statistics for key variables in our sample, covering the period 2000-2021. All ratio variables are winsorized at the 1% level in both tails to reduce the influence of outliers. Variable definitions and data sources are described in Appendix C.

				Distribution		
	N	Mean	SD	$P10$	Median	$P90$
Investment	76,227	397	1,945	6	58	643
Capital	72,466	3,983	19,144	44	439	6,631
Investment rate	68,030	0.18	0.15	0.05	0.13	0.34
Q	67,999	1.28	1.87	0.02	0.72	2.94
CF	67,960	0.12	0.19	-0.07	0.12	0.31
Sales growth	70,982	0.12	0.41	-0.20	0.04	0.44
Total assets (log)	76,325	6.07	1.99	3.47	6.03	8.76
Leverage	75,993	0.39	0.42	0.00	0.31	0.88
Cash/assets	76,320	0.19	0.21	0.01	0.11	0.54
OwnPassive (%)	54,048	5.92	6.06	0.24	3.79	14.99
OwnETF (%)	51,214	2.46	3.01	0.07	1.32	6.42
OwnQIX (%)	58,358	38.55	22.97	5.82	40.43	68.13
OwnDED (%)	39,173	3.89	7.17	0.01	0.76	11.49
OwnTRA (%)	57,542	14.87	10.45	1.57	13.87	29.32
RETVOL	54,845	0.03	0.02	0.01	0.03	0.06
INCVOL	49,340	0.02	0.03	0.00	0.01	0.05
R&D Intensity	46,653	0.09	0.13	0.00	0.04	0.24
Firm age (log)	76,323	2.66	0.87	1.61	2.71	3.81
Shock	76,282	0.06	0.08	-0.03	0.06	0.13

Table 2: Investment Rates by Passive Ownership Tercile

This table reports investment patterns across terciles formed annually based on the percentage of shares held by passive investors. Panel A presents mean investment rates by passive ownership tercile. Panel B reports the average persistence parameter ρ from AR(1) model of log-investment, estimated using 5-year rolling windows. Panels C and D report persistence estimates from dynamic panel regressions, where the dependent variable is log-investment in Panel C and the investment rate in Panel D. Panel E reports the coefficients on Tobin's Q and cash flow (CF) from investment regressions. Variable definitions are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Passive Ownership Category →	Low	Medium	High
Mean Passive Ownership (%)	1.384	5.626	10.764
Panel A: Investment Rates			
$^{\mu}$Investment rate	0.186	0.185	0.159
$^{\sigma}$Investment rate	0.160	0.153	0.120
Panel B: Investment Persistence			
Average ρ AR(1) LnInvest	0.363	0.467	0.505
Panel C: Arellano-Bond estimation (LnInvest)			
LnInvest_{t-1}	0.294***	0.360***	0.429***
	(0.033)	(0.028)	(0.031)
Observations	12,818	14,576	15,316
χ^2	479.26	1580.78	2916.08
Panel D: Arellano-Bond estimation (InvestmentRate)			
$\text{InvestmentRate}_{t-1}$	0.333***	0.381***	0.440***
	(0.018)	(0.022)	(0.028)
Observations	12,768	14,527	15,259
χ^2	594.19	740.92	666.41
Panel E: Investment Regressions			
Q_{it-1}	0.031***	0.027***	0.022***
	(0.002)	(0.001)	(0.001)
CF_{it}^{tot}	0.103***	0.070***	0.139***
	(0.012)	(0.014)	(0.013)
Observations	14,164	15,822	16,985
Adj R-squared	0.62	0.73	0.76
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 3:
Baseline Investment Regressions

This table reports panel regression estimates of investment rates on Tobin's Q, cash flow, passive ownership, and their interactions. The dependent variable is total investment scaled by beginning-of-year capital stock. Control variables include lagged sales growth, firm size (log of assets), leverage, and cash holdings. Firm and year fixed effects are included in all specifications. Variable definitions are provided in Appendix C. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable $\rightarrow$ Investment Rate $\frac{I_{i,t}}{K_{i,t-1}}$				
	(1)	(2)	(3)	(4)
$\text{OwnPassive}_{i,t} \times Q_{i,t-1}$	-0.125***	-0.137***	-0.137***	-0.152***
	(0.009)	(0.009)	(0.009)	(0.011)
$Q_{i,t-1}$	0.041***	0.039***	0.039***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{OwnPassive}_{i,t}$	0.141***	0.160***	0.160***	0.123***
	(0.022)	(0.022)	(0.022)	(0.023)
$\text{CF}_{i,t}$		0.089***	0.089***	0.073***
		(0.008)	(0.008)	(0.010)
$\text{OwnPassive}_{i,t} \times \text{CF}_{i,t}$				0.411***
				(0.117)
Observations	50,092	50,052	50,052	50,052
Adj R-squared	0.68	0.68	0.68	0.68
Controls	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 4:
Investment Regressions by Firm Characteristics

This table reports the sensitivity of investment to Tobin's Q across terciles of passive ownership, for firm categories sorted by return volatility, income volatility, and R&D intensity. $\texttt{DPassive}^{Top}$ is a binary indicator equal to one for firms in the top-third of passive ownership in a given year, and zero otherwise. $\texttt{DPassive}^{Bottom}$ is defined analogously for firms in the bottom third. All specifications include firm and year fixed effects. Standard errors, reported in parentheses, are clustered at the firm level. Variable definitions are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable → Investment Rate $\frac{I_{i,t}}{K_{i,t-1}}$						
	Return Volatility		Income Volatility		R&D Intensity	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{DPassive}_{i,t}^{Top} \times Q_{it-1}$	0.002**	-0.001	0.003	0.001	0.002	-0.003*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
$\text{DPassive}_{i,t}^{Bottom} \times Q_{it-1}$	0.003	0.007***	0.002	0.007**	0.010**	0.009***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)	(0.002)
$\text{DPassive}_{i,t}^{Top}$	-0.004**	0.003	-0.004*	0.003	-0.004	0.006
	(0.002)	(0.004)	(0.002)	(0.003)	(0.003)	(0.005)
$\text{DPassive}_{i,t}^{Bottom}$	0.001	-0.004	-0.004	-0.011***	-0.007*	-0.009**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Q_{it-1}	0.009***	0.036***	0.018***	0.027***	0.023***	0.033***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
CF_{it}^{tot}	0.198***	0.062***	0.172***	0.084***	0.165***	0.024**
	(0.013)	(0.010)	(0.014)	(0.011)	(0.021)	(0.011)
Observations	16,519	15,880	15,119	14,824	12,481	12,352
Adj R-squared	0.72	0.66	0.73	0.61	0.63	0.71
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5:
Investment Dynamics: Autoregressive Specifications

This table reports estimates from dynamic panel regressions of investment rates that include lagged investment as a regressor. The dependent variable is capital expenditures scaled by beginning-of-year capital stock. Column (1) uses the full sample. Columns (2) and (3) split the sample based on passive ownership (below and above the median). The long-run response to Q is calculated as $\alpha_q/(1-\lambda)$. Standard errors are clustered at the firm level and reported in parentheses. Variable definitions are provided in Appendix C. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable $\rightarrow$ Investment Rate $\frac{I_{i,t}}{K_{i,t-1}}$				
		Passive Ownership Terciles		
	Full sample	Bottom	Medium	Top
	(1)	(2)	(3)	(4)
L.Investment rate	0.346***	0.246***	0.298***	0.321***
	(0.009)	(0.017)	(0.018)	(0.021)
Q_{it-1}	0.018***	0.027***	0.021***	0.016***
	(0.001)	(0.003)	(0.001)	(0.002)
Cash flow	0.084***	0.090***	0.052***	0.118***
	(0.010)	(0.018)	(0.016)	(0.015)
Observations	50,305	12,132	14,125	15,104
χ^2	4886.18	788.32	1065.26	1012.22
Controls	Yes	Yes	Yes	Yes

Table 6:
Investment Response to Industry Shocks

This table presents estimates from regressions of investment rates on industry shocks and their interactions with passive ownership. The dependent variable is capital expenditures scaled by beginning-of-year capital stock. Columns (2) and (3) present results separately for firms in the bottom and top terciles of passive ownership, defined annually. Columns (1)-(4) include firm and year fixed effects, while Columns (5) and (6) replace year fixed effects with industry-year fixed effects. Column (6) further excludes industries with high passive ownership. Standard errors, clustered at the firm level, are reported in parentheses. Variables definitions are provided in Appendix C. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable $\rightarrow$ Investment Rate $\frac{I_{i,t}}{K_{i,t-1}}$						
		Passive ownership in the bottom-third	Passive ownership in the Top-third	Including firm and year fixed-effects	Including firm and industry-year fixed-effects	Excluding industries with OwnPassive >75th%ile
	(1)	(2)	(3)	(4)	(5)	(6)
Shock$_{j,t-1}$	0.061***	0.090***	0.037**	0.071***	0.035	0.057
	(0.011)	(0.023)	(0.015)	(0.012)	(0.085)	(0.093)
Shock$_{j,t-1}$ $\times$ DPassive$_{i,t}^{Top}$				-0.034**	-0.027**	-0.057***
				(0.014)	(0.014)	(0.016)
DPassive$_{i,t}^{Top}$				0.005***	0.003*	0.008***
				(0.002)	(0.002)	(0.002)
CF$_{i,t}$	0.161***	0.108***	0.270***	0.161***	0.156***	0.154***
	(0.008)	(0.016)	(0.015)	(0.008)	(0.008)	(0.009)
Observations	67,041	15,767	17,296	67,041	67,031	49,762
Adj R-squared	0.58	0.56	0.68	0.58	0.60	0.58
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	No
Industry-Year FE	No	No	No	No	Yes	Yes

Table 7: Economic Magnitudes of Passive Ownership Effects

	Investment Change (USD millions)		
Scenario	Net Effect	Direct	Interaction
Panel A: Median Firm ($439M Capital)			
One SD increase in OwnPassive (6 ppts):			
Q = 0.72 (median)	+1.6	+3.2	-1.6
Q = 2.95 (90th pctile)	-8.9	+3.2	-12.1
Panel B: Large Firm (90th pctile, $6.63B)			
One SD increase in OwnPassive (6 ppts):			
Q = 2.95 (90th pctile)	-134.7	+49.0	-183.7
Panel C: Demand Shock Response			
75th percentile shock (0.15), median firm:			
Low passive ownership	+10.9		
High passive ownership	+7.3		
Difference	-3.6		

Panel A and B use Table 3 estimates: OwnPassive = 0.123, OwnPassive $\times$ Q = -0.152. Panel C uses Table 6 estimates: low passive ownership shock sensitivity = 0.090, high passive ownership = 0.037 (calculated as 0.090 - 0.034). Capital stock values from Table 1. Net effect = Direct + Interaction.

Appendix

A Appendix: Model Setup

This appendix provides the formal setup of the model used in Section 2.

A.1 Agents

There are three types of agents: ultimate investors, fund managers, and firms.

Ultimate investors. Each investor j is characterized by a type vector

$$\varphi_j = (c_j, g_j, \ell_j), \tag{A.1}$$

where c_j denotes fee sensitivity, g_j preference for monitoring, and ℓ_j preference for liquidity. Investors allocate wealth between active and passive/index funds according to these preferences.

Fund managers. There are three types of managers $\tau \in \{A, P, I\}$.

1. *Active managers* (A): choose portfolios endogenously and provide monitoring at cost f_A.
2. *Passive managers* (P): hold diversified portfolios without monitoring, charging low fees f_P.
3. *Index managers* (I): replicate index weights w_i^{index}, with very low fees and no discretion.

Firms. Each firm i is defined by type

$$\theta_i = (\sigma_i, \kappa_i, \mu_i), \tag{A.2}$$

where σ_i is business volatility, κ_i governance complexity, and μ_i the incremental value from active monitoring.

A.2 Matching Technology

Let $\mu(i, \tau)$ denote the fraction of firm i's equity held by manager type τ. The surplus from matching i and τ is

$$S(\theta_i, \tau) = \Pi(\theta_i, \tau) - C(\theta_i, \tau) - M(\theta_i, \tau), \tag{A.3}$$

where Π is value creation, C direct costs, and M a mismatch penalty.

Mismatch costs are quadratic.

$$M(\theta_i, \tau) = \eta \|\theta_i - \theta_\tau^*\|^2, \quad \eta > 0, \tag{A.4}$$

with θ_τ^* the firm type best suited to manager τ.

The profit and cost components are

$$\Pi(\theta_i, A) = \bar{\pi} + \mu_i - \kappa_i^2/2, \qquad C(\theta_i, A) = c_A + \xi\kappa_i, \tag{A.5}$$

$$\Pi(\theta_i, P) = \bar{\pi}, \qquad C(\theta_i, P) = c_P, \tag{A.6}$$

$$\Pi(\theta_i, I) = \bar{\pi} - \delta_I \cdot 1[\text{Index}_{it} = 0], \qquad C(\theta_i, I) = c_I. \tag{A.7}$$

A.3 Equilibrium

The equilibrium is defined as the surplus-maximizing allocation in a transferable utility matching market between heterogeneous firms and fund manager types. There is endogenous sorting that maximizes aggregate surplus subject to market clearing constraints via shadow prices.

Equilibrium matches maximize total surplus subject to market clearing.

$$\frac{\partial S(\theta_i, \tau)}{\partial \mu(i, \tau)} = \lambda_\tau, \quad \forall i, \tau, \tag{A.8}$$

where λ_τ is the shadow value of capital from type τ managers.

The equilibrium passive ownership share of firm i is

$$\alpha_i = \frac{\sum_{\tau=P} \mu(i, \tau)}{\sum_\tau \mu(i, \tau)}. \tag{A.9}$$

Index inclusion is modeled as

$$\text{Index}_{it} = 1\{\|\theta_i - \theta_I^*\| \leq \varepsilon\}, \tag{A.10}$$

where ε is a tolerance parameter. Inclusion mechanically raises α_i regardless of firm characteristics.

B Appendix: Proofs of Propositions

This appendix provides formal proofs of the propositions stated in Section 2.

Proof of Proposition 1 (Investment-Q Sensitivity)

Firm i chooses investment I_i to maximize

$$\max_{I_i} \; q_i I_i - \tfrac{1}{2}(\omega_0 + \gamma\alpha_i)\Big(\tfrac{I_i}{K_i}\Big)^2 K_i. \tag{A.11}$$

The first-order condition is

$$q_i - (\omega_0 + \gamma\alpha_i)\,\frac{I_i}{K_i} = 0, \tag{A.12}$$

implying

$$\frac{\partial(I_i/K_i)}{\partial q_i} = \frac{1}{\omega_0 + \gamma\alpha_i}. \tag{A.13}$$

Since $\gamma > 0$, the sensitivity is strictly decreasing in α_i. □

Proof of Proposition 2 (Heterogeneous Effects)

The incremental benefit of active monitoring is μ_i, and monitoring costs rise with governance complexity κ_i. The surplus function satisfies

$$\frac{\partial S(\theta_i, A)}{\partial \mu_i} > 0, \quad \frac{\partial S(\theta_i, A)}{\partial \kappa_i} < 0, \tag{A.14}$$

so high-μ_i, high-κ_i firms optimally match with active managers. If such firms are forced to higher α_i, investment-Q sensitivity falls more sharply because $\partial(I_i/K_i)/\partial q_i$ is more responsive to α_i. □

Proof of Proposition 3 (Index Shocks and Mismatch)

Index inclusion raises α_i mechanically,

$$\Delta\alpha_i > 0 \quad \text{if} \quad \text{Index}_{it} = 1. \tag{A.15}$$

From Proposition 1,

$$\Delta\Big(\frac{\partial(I_i/K_i)}{\partial q_i}\Big) = -\frac{\gamma\Delta\alpha_i}{(\omega_0 + \gamma\alpha_i)^2}. \tag{A.16}$$

The decline is most severe for firms with high μ_i and κ_i, since their optimal match is active ownership. Hence index shocks generate mismatches that lower responsiveness disproportionately for such firms. □

Proof of Proposition 4 (Adjustment Dynamics)

Consider the dynamic specification

$$\frac{I_{it}}{K_{i,t-1}} = \lambda \frac{I_{i,t-1}}{K_{i,t-2}} + \beta_Q q_{i,t-1} + \varepsilon_{it}. \tag{A.17}$$

From the adjustment cost function, higher α_i raises effective convexity and slows convergence. Thus

$$\frac{\partial \lambda}{\partial \alpha_i} > 0, \tag{A.18}$$

implying that higher passive ownership is associated with more persistent investment dynamics. □

Next we summarizes the testable predictions derived from the model in Section 2. Each implication maps directly to the empirical specifications in Section 5.

1. **Investment-Q Sensitivity.** From Proposition 1.

$$\frac{\partial (I_i/K_i)}{\partial Q_i} = \frac{1}{\omega_0 + \gamma \alpha_i}, \qquad \gamma > 0. \tag{A.19}$$

   Prediction: in regressions of investment on Q, the interaction $Q \times \alpha_i$ enters with a negative coefficient.

2. **Heterogeneous Effects.** From Proposition 2. The marginal effect of passive ownership is larger for firms with higher monitoring value μ_i and governance complexity κ_i. Prediction: triple interactions $Q \times \alpha_i \times Z_i$ are negative when Z_i proxies for monitoring needs (e.g., R&D intensity, volatility).

3. **Index Inclusion.** From Proposition 3. Index events exogenously raise α_i, creating mismatches. Prediction: regressions around index inclusions should show a stronger decline in Q sensitivity for high-μ_i, high-κ_i firms.

4. **Adjustment Dynamics.** From Proposition 4. Higher α_i increases persistence in investment

adjustment. Prediction: in dynamic panels,

$$\frac{I_{it}}{K_{i,t-1}} = \lambda \frac{I_{i,t-1}}{K_{i,t-2}} + \beta_Q Q_{i,t-1} + \beta_{Q\alpha}(Q_{i,t-1} \times \alpha_{it}) + \varepsilon_{it}, \tag{A.20}$$

the coefficient λ rises with α_i.

These implications provide the direct link between the model and our empirical design in Section 5.

C Appendix: Variable Definitions

Data sources for firm characteristics are from Compustat, CRSP Mutual Fund database, and Thomson Reuters S12.

Panel A: Investment, Q, and cash flows

Total investment rate Defined as $\frac{I^{tot}_{i,t}}{K^{tot}_{f,t-1}}$, where total investment (I^{tot}) is the sum of capital expenditures (*capx*) and intangible investment, measured as R&D expenses plus 30% of SG&A expenses excluding R&D ($xrd + 0.3 \times (xsga - xrd)$). Total capital ($K^{tot}$) is the sum of the book value of property, plant, and equipment (*ppegt*) and intangible capital from Peters and Taylor (2017) via WRDS. Intangible capital equals externally purchased intangibles (*intan*) plus internally created intangibles, estimated using the perpetual inventory method by accumulating past R&D expenses and a portion of SG&A excluding R&D. See Eisfeldt and Papanikolaou (2014) and Peters and Taylor (2017) for more details.

Total Q Defined as firm value (V) divided by total capital (K^{tot}). Firm value equals the market value of equity (*prcc_f* $\times$ *csho*) plus the book value of debt (*dltt* + *dlc*), minus current assets (act). Total capital K^{tot} is as defined above.

Cash flow rate Defined as $\frac{CF_{f,t}}{K^{tot}_{f,t-1}}$ where cash flow (CF) is operating income before extraordinary items plus depreciation expenses, plus the after-tax cost of intangible investment: oibdp + (xrd+0.3 $\times$ (xsga-xrd)) $\times$ (1-τ_C), with τ_C as the corporate tax rate, assumed to be 30%. Total capital K^{tot} is as defined above.

Panel B: Ownership Variables

OwnPassive The aggregate fraction of a firm's outstanding shares held by mutual funds pursuing passive investment strategies. Passive ownership is estimated using mutual fund data from Thomson Reuters S12 and outstanding shares from CRSP. Funds are classified as passive using two methods: (1) the CRSP Mutual Fund database's index fund flag, with values "B," "D," or "E"; and (2) the Appel et al. (2016) name-based rule, identifying funds whose names contain any of the following strings: "Index", "Idx", "Indx", "Ind", "Russell", "S & P", "S and P", "S&P", "SandP", "DOW", "Dow", "DJ", "MSCI", "Bloomberg", "KBW", "NASDAQ", "NYSE", "STOXX", "FTSE", "Wilshire", "Morningstar", "100", "400", "500", "600", "900", "1000", "1500", "2000", and "5000". The Thomson Reuters S12 mutual fund holdings data are then used to compute the share of each firm's stock owned by passive mutual funds.

OwnETF The aggregate fraction of a firm's outstanding shares held by ETFs, with ETFs identified in CRSP data as those with et_flag=F and with share code=73, restricting to U.S. domestic equity funds. To isolate domestic equity funds, we exclude any fund whose Lipper

class in CRSP contains the following keywords: "International," "Canada," "Australia," "Austria," "Belgium," "France," "Hong Kong," "Malaysia," "Netherlands," "Singapore," "Sweden," "Switzerland," "Italy," "Spain," "U.K.," "Mexico," "Brazil," "Thailand," "Turkey," "Germany," "Russia," "BRIC," "Global," "World," "Japan," "Japanese," "European," "Emerging Markets," "China," "India," "Latin," "World," "Pacific," "Leverage," "Short Bias," "Alternative," "Mixed Asset," "Gold," "Natural Resources," "Real Estate," "ADR,", "Develop," or "Europe." Following Antoniou et al. (2023), we manually reviewed the ETF list. ETFs are classified as market ETFs if their names indicate they track broad market indexes (identified by the keyword "broad"). ETFs tracking sector index or non-market indexes (e.g., Russell 1000 Value Index) are classified as non-market ETFs. While both track indexes, non-market ETFs do not follow broad-market indexes.

OwnQIX Percentage of shares outstanding held by quasi-indexers, as classified by Brian Bushee. These institutions exhibit low portfolio turnover and highly diversified holdings, consistent with a passive, buy-and-hold investment strategy. See Bushee and Noe (2000) and Bushee (2001) for details. Data sourced from Bushee's website.

OwnDED Percentage of shares outstanding held by dedicated institutions (DED), which take large positions in a small number of firms and maintain low portfolio turnover. These investors are characterized by concentrated holdings and long-term engagement. See Bushee and Noe (2000) and Bushee (2001). Data sourced from Bushee's website.

OwnTRA Percentage of shares outstanding held by transient institutions, identified by high portfolio turnover and diversified holdings. These investors typically pursue short-term trading strategies. See Bushee and Noe (2000) and Bushee (2001). Data sourced from Bushee's website.

Panel C: Other Variables

Sales growth $\left(\frac{S_{ft}-S_{ft-1}}{S_{ft-1}}\right)$ Annual growth in sales, with values deflated to constant 2012 dollars using the GDP deflator from FRED.

Size Log of real assets.

Leverage Book debt (*dltt* + *dlc*) divided by the sum of book debt and market equity (*prcc_f* $\times$ *csho*).

Tangibility Net property, plant and equipment (*ppent*) divided by assets (*at*).

Cash Cash and marketable securities (*che*) divided by assets (*at*). If *che* is missing, it is estimated as cash (*ch*) plus marketable securities (*ivst*).

Return Volatility (RETVOL) Standard deviation of excess daily returns over a 45-day window ending 11 days before the earnings announcement date, averaged over the past four quarters.

Income Volatility (INCVOL) Standard deviation of changes in quarterly income (*qibdpq*) divided by quarterly assets (*atq*), using the past 20 quarters with a minimum of 8 observations.

R&D Intensity R&D expense (*xrd*) divided by assets (*at*).

Age Number of years since the firm first appeared on Compustat.

Shock Industry-level demand shocks constructed using upstream input-output (IO) linkages from the Bureau of Economic Analysis (BEA). Starting with the "make" table (industry-by-commodity), we compute the share of commodity c produced by industry j as the ratio of the dollar value of c produced by j to the total production of c across all industries. Multiplying this share matrix by the "use" table (commodity-by-industry) yields an industry-by-industry matrix of dollar flows from producer industry j to consumer industry k. We normalize each row by the total sales of the producing industry to obtain the "customer" matrix: $\omega_{jk} = \frac{\text{sales from j to k}}{\text{total sales of j}}$, where ω_{jk} represents the share of industry j's output purchased by industry k. Using these weights, we define the **demand shock** for industry j at time t as: $\text{Shock}_{jt} = \sum_{k \neq j} \omega_{jk} \Delta\text{Sales}_{kt}$, where ΔSales_{kt} is the percentage change in industry k's sales. We exclude within-industry flows ($k = j$) to isolate external demand variation. The resulting measure captures cross-industry demand shocks weighted by observed supply-chain linkages.

Internet Appendix for

"Passive Ownership and Corporate Investment:
A Matching Perspective"

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IA Advantages of Our Demand Shock Approach

IA.1 Cleaner Identification

The industry demand shock variable offers several methodological advantages over traditional Tobin's Q measures, enhancing the credibility of our empirical identification. Most importantly, these shocks originate from *upstream industries* via input-output linkages, introducing variation that is largely orthogonal to firm-specific factors that might be potentially correlated with ownership structure. This orthogonality addresses a key limitation of Tobin's Q, which may reflect endogenous firm-traits that influence both investment behavior and investor composition.

A second advantage is the temporal clarity of demand shocks. Unlike Tobin's Q, which embeds market expectations and may be correlated with ownership choices, demand shocks represent discrete, identifiable changes in economic fundamentals that are exogenous to firm-level decisions. This temporal precision allows for a cleaner measurement of how firms with different ownership structures respond to investment opportunities.

Finally, by excluding within-industry flows and focusing solely on cross-industry linkages, the shock variable mitigates concerns about common industry-level factors that could simultaneously affect both ownership structure and investment. This design choice strengthens identification by reducing the risk of confounding from shared industry dynamics. This is a common challenge in the passive ownership literature.

IA.2 Measurement Precision

The construction of our demand shock variable addresses several empirical challenges that have complicated previous research on ownership and investment. We use two-digit NAICS codes rather than more granular six-digit classifications. This is a deliberate trade-off between precision and measurement error. While finer industry classifications may appear preferable, they introduce substantial noise due to frequent reclassifications and compositional shifts unrelated to underlying demand conditions. Aggregating at the two-digit level reduces this noise while preserving economically meaningful variation in upstream demand that plausibly affects downstream investment.

The bounded nature of the shock variable (ranging from -1 and 1) further enhances its

empirical reliability. These bounds arise naturally from our construction methodology and help avoid extreme outliers that often result from more granular industry definitions. This feature ensures that our identification strategy captures normal business cycle variation, rather than rare or exceptional events that may not reflect typical firm-investor dynamics. As a result, our estimates are more externally valid and applicable to routine investment behavior.

Our weighting scheme, based on actual input-output relationships, ensures that our demand shocks reflect real economic linkages rather than arbitrary industry groupings. This grounding in supply chain data strengthens the theoretical justification for our identification strategy, as the variation we exploit corresponds to economically meaningful connections that should influence firm-level investment decisions. The use of Bureau of Economic Analysis input-output tables provides an objective, government-sourced measure of these relationships, reducing concerns about researcher discretion in variable construction and enhancing the credibility of our empirical design.

IA.3 Dynamic Response Patterns

The demand shock evidence enables us to test richer dynamic predictions from the matching model, extending beyond static differences in investment sensitivity. The theoretical framework generates specific predictions about how firms with different ownership structures should respond to external opportunities over time, providing multiple dimensions along which to evaluate the matching hypothesis.

Firms with high passive ownership are predicted to exhibit lower initial responsiveness to demand shocks, consistent with their optimized governance structures that prioritize stability and cost minimization over rapid adjustment. This initial response differential represents the most direct test of our matching model's core prediction, but the dynamic framework suggests that this immediate effect is only part of the story. The matching model predicts that while high passive ownership firms respond less aggressively in the short term, this reduced responsiveness reflects an optimal trade-off rather than a constraint that prevents appropriate long-term adjustment.

Despite different adjustment speeds, both ownership types should eventually reach appropriate investment levels, reflecting the efficiency of their respective matching equilibria. This convergence prediction distinguishes our matching framework from models that would predict permanent differences in investment levels across ownership structures. The efficiency interpretation suggests that firms with different ownership structures should reach similar long-run

responses to persistent demand changes, even though they follow different adjustment paths to reach those outcomes.

The adjustment process should be more gradual for high passive ownership firms, but this persistence should reflect optimal smoothing rather than inefficient delays. The matching model predicts that the extended adjustment period represents a conscious choice to minimize adjustment costs and maintain stable relationships with low-cost capital providers, rather than an inability to respond appropriately to changing conditions. This distinction has important implications for welfare analysis and policy conclusions.

IA.4 Cross-Sectional Heterogeneity

The matching framework generates specific predictions about when ownership effects should be strongest, providing additional dimensions for empirical testing. The theoretical model suggests that the relationship between ownership structure and investment responsiveness should vary systematically with firm and industry characteristics that determine the value of different governance arrangements.

$$\frac{\partial}{\partial \alpha}\left(\frac{\partial I/K}{\partial \text{Shock}}\right) = f(\text{Industry Characteristics}, \text{Firm Characteristics}) \tag{A.1}$$

The effect should be most pronounced for firms in industries where monitoring provides significant value, since these firms benefit most from the intensive oversight that active ownership provides and suffer most when forced into passive ownership arrangements. Similarly, firms with complex operational structures that require specialized governance should exhibit stronger ownership effects, as the match quality between firm needs and investor capabilities becomes more crucial with increasing governance complexity.

Firms facing significant coordination costs among stakeholders represent another category where ownership effects should be particularly pronounced. The matching model suggests that these firms optimally sort into ownership structures that minimize coordination frictions, making the match between firm characteristics and investor capabilities especially important for performance outcomes. Testing these cross-sectional predictions provides additional validation of the matching framework beyond the basic prediction of differential investment sensitivity.

IA.5 Integration with Existing Evidence

Complementary Identification Strategies The demand shock approach complements rather than replaces existing identification strategies, creating opportunities for more comprehensive empirical analysis that exploits multiple sources of variation. Combining different strategies enhances robustness and helps address distinct endogeneity concerns that may affect individual strategies.

In particular, integrating demand shock analysis with Russell index inclusion events provides two independent sources of exogenous variation. Index inclusion mechanically alters a firm's ownership structure by triggering passive fund purchases, while demand shocks introduce variation in investment opportunities through upstream industry linkages. This dual approach strengthens causal inference: if both strategies yield consistent results, it reinforces the validity of the underlying theoretical relationships.

A comprehensive empirical approach would use Russell index inclusion as an instrument for passive ownership, then examine how instrumented ownership interacts with demand shocks to affect investment behavior. The first stage would estimate how index inclusion affects passive ownership through the mechanical purchases required by index funds:

$$\text{OwnPassive}_{it} = \alpha + \pi \text{IndexInclusion}_{it} + \theta X_{it} + \eta_{it} \tag{A.2}$$

The second stage would then examine how this instrumented variation in ownership structure affects the responsiveness to demand shocks:

$$\frac{I_{it}}{K_{it-1}} = \beta_0 + \beta_1 \text{Shock}_{jt} + \beta_2 \widehat{\text{OwnPassive}}_{it} \times \text{Shock}_{jt} + \gamma X_{it} + \varepsilon_{it} \tag{A.3}$$

This two-stage framework addresses concerns about the endogenous sorting that drives ownership choices while testing the fundamental prediction that ownership structure affects investment responsiveness to external opportunities.

Robustness and External Validity The demand shock evidence enhances the robustness of our findings by providing validation across multiple dimensions, thereby strengthening confidence in the underlying theoretical relationships. The consistency of results across different empirical approaches suggests that the observed patterns reflect fundamental economic relationships rather than artifacts of particular identification strategies or sample characteristics.

Finding consistent results across both Q-based and shock-based opportunity measures strengthens confidence in the underlying relationship between ownership structure and investment responsiveness. Since these measures capture different aspects of investment opportunities and are subject to different types of measurement error and endogeneity concerns, consistency across approaches suggests that the results reflect genuine economic relationships rather than methodological artifacts.

The cross-industry nature of demand shocks allows testing whether the ownership effects hold across different economic sectors and supply chain structures, providing evidence on the external validity of the matching framework. If the theoretical relationship reflects fundamental aspects of how different ownership structures affect corporate behavior, it should be evident across diverse industry settings rather than concentrated in particular sectors where unique institutional features might drive the results.

The consistent relationship between ownership and shock responsiveness over time supports the matching framework's prediction of stable equilibrium relationships that persist as markets develop and institutional arrangements evolve. This temporal stability suggests that the observed patterns reflect fundamental economic forces rather than temporary market conditions or regulatory changes that might affect particular time periods.

IB Robustness: Alternative Measures of Passive Ownership

This table presents robustness tests using alternative measures of ownership. Column (1) reports baseline estimates using our main passive ownership measure (corresponding to column (4) of Table 3). Column (2) uses ETF holdings only. Column (3) uses Quasi-indexer ownership as defined by Brian Bushee (Bushee, 2001). Columns (4) and (5) use two additional institutional investor categories from Bushee: Column (4) measures ownership by dedicated institutions, while Column (5) uses transient ownership. All specifications include the full set of controls and fixed effects from our baseline specification in Table 3, column (4). Variable definitions are provided in Appendix C.

	Ownership Measure (`Ownership`):				
	Baseline (OwnPassive)	ETFs (OwnETF)	Quasi-indexer (OwnQIX)	Dedicated (OwnDED)	Transient (OwnTRA)
	(1)	(2)	(3)	(4)	(5)
$\texttt{Ownership}_{i,t} \times Q_{i,t-1}$	-0.152***	-0.266***	-0.043***	0.012	-0.028***
	(0.011)	(0.023)	(0.003)	(0.015)	(0.007)
$Q_{i,t-1}$	0.040***	0.037***	0.048***	0.032***	0.037***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
$\texttt{Ownership}_{i,t}$	0.123***	0.219***	0.031***	-0.071***	0.063***
	(0.023)	(0.041)	(0.006)	(0.018)	(0.012)
CF_{it}	0.073***	0.080***	0.063***	0.073***	0.068***
	(0.010)	(0.010)	(0.013)	(0.010)	(0.012)
$\texttt{Ownership}_{i,t} \times \text{CF}_{i,t}$	0.411***	0.698***	0.104***	0.060	0.100
	(0.117)	(0.223)	(0.028)	(0.084)	(0.063)
Observations	50,052	47,842	53,598	36,030	52,837
Adj R-squared	0.68	0.69	0.68	0.70	0.67
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

IC Effect of Passive Ownership on Investment-Q Sensitivity: Sorts on Firm Size and Age

	Firm Age		Firm Size	
	Young	Old	Small	Large
	(1)	(2)	(3)	(4)
$\text{DPassive}_{i,t}^{Top} \times Q_{it-1}$	0.000	0.001	-0.001	0.001
	(0.002)	(0.001)	(0.004)	(0.002)
$\text{DPassive}_{i,t}^{Bottom} \times Q_{it-1}$	0.004**	0.002	0.007***	0.007
	(0.002)	(0.003)	(0.002)	(0.005)
$\text{DPassive}_{i,t}^{Top}$	0.004	0.000	0.007	-0.002
	(0.005)	(0.002)	(0.009)	(0.002)
$\text{DPassive}_{i,t}^{Bottom}$	-0.005	-0.001	0.001	-0.006
	(0.004)	(0.002)	(0.003)	(0.005)
Q_{it-1}	0.036***	0.016***	0.032***	0.027***
	(0.001)	(0.001)	(0.001)	(0.002)
CF_{it}^{tot}	0.036***	0.158***	0.033***	0.144***
	(0.011)	(0.011)	(0.011)	(0.014)
Observations	16,695	23,073	19,019	21,856
Adj R-squared	0.68	0.58	0.61	0.68
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

ID Investment Regressions by Sub-periods: 2000-2021

This table reports panel regression estimates of investment rates on Tobin's Q, cash flow, passive ownership, and their interactions for subperiods. The dependent variable is total investment scaled by beginning-of-year capital stock. Control variables include lagged sales growth, log of assets, leverage, and cash holdings. Standard errors clustered at the firm level are reported in parentheses. Variable definitions are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Sub-periods			
	2000-05	2006-10	2011-15	2016-21
	(1)	(2)	(3)	(4)
Q_{it-1}	0.033***	0.028***	0.030***	0.028***
	(0.002)	(0.003)	(0.005)	(0.004)
CF_{it}	0.049***	0.069***	0.095***	0.071***
	(0.017)	(0.018)	(0.034)	(0.023)
OwnPassive	0.295**	0.264***	0.132***	0.128***
	(0.117)	(0.073)	(0.044)	(0.038)
OwnPassive $\times$ Q_{it-1}	-0.152***	-0.128***	-0.072**	-0.069***
	(0.054)	(0.035)	(0.036)	(0.024)
OwnPassive $\times$ CF_{it}	1.048*	0.514*	-0.257	0.072
	(0.625)	(0.273)	(0.309)	(0.164)
Observations	13,375	12,152	10,165	11,762
Adj R-squared	0.72	0.73	0.80	0.83
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

IE Demand Shocks and Passive Ownership

This table tests whether industry demand shocks predict changes in passive ownership. The dependent variable is the change in the passive ownership share, $\Delta\alpha_{it}$. Industry Demand Shock$_{j,t-1}$ is the instrument used in the investment regressions. Firm controls include size, leverage, and cash holdings. Standard errors are clustered by firm. Coefficients are small and statistically insignificant across specifications, supporting the exclusion restriction that demand shocks affect investment only through Tobin's Q, not through ownership composition. Variable definitions are provided in Appendix C.

	Dependent Variable: Change in Passive Ownership Share $\Delta\alpha_{it}$			
	(1)	(2)	(3)	(4)
Shock$_{j,t-1}$	0.002	0.000	-0.001	0.009
	(0.003)	(0.003)	(0.003)	(0.017)
Observations	45,439	44,695	43,546	44,681
Adj R-squared	0.05	0.08	0.08	0.09
Controls	No	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No
Industry-Year FE	No	No	No	Yes

IF Measuring Magnitudes

This appendix quantifies the economic significance of passive ownership effects on corporate investment behavior using the empirical estimates from our baseline specifications. There are two questions. (1) What is the dollar impact of changes in passive ownership on corporate investment? (2) How does passive ownership affect the timing of investment adjustment following economic shocks?

IF.1 Effect on Investment in Dollar Terms

We calculate the marginal effect of passive ownership changes on investment rates using the baseline regression estimates from Table 3, Column (4). The estimated relationship is,

$$\frac{I_{it}}{K_{it-1}} = \beta_0 + \beta_Q Q_{it-1} + \beta_\alpha \text{OwnPassive}_{it} + \beta_{\alpha Q}(\text{OwnPassive}_{it} \times Q_{it-1}) + \text{controls} \tag{A.4}$$

where $\beta_\alpha = 0.123$ and $\beta_{\alpha Q} = -0.152$. For a one standard deviation increase in passive ownership (6 percentage points), the change in investment rate is,

$$\Delta\left(\frac{I_{it}}{K_{it-1}}\right) = 0.06 \times (0.123 - 0.152 \times Q_{it-1}) \tag{A.5}$$

We evaluate this expression at representative firm characteristics. Using the median capital stock of \$439 million from Table 1 avoids bias from the right-skewed firm size distribution that would arise from using mean values.

Median Investment Opportunities ($Q = 0.724$)

$$\Delta\left(\frac{I_{it}}{K_{it-1}}\right) = 0.06 \times (0.123 - 0.152 \times 0.724) = 0.06 \times 0.013 = 0.0008 \tag{A.6}$$

$$\Delta I_{it} = 0.0008 \times 439 = \$0.35 \text{ million} \tag{A.7}$$

High Investment Opportunities (75th percentile, $Q = 1.543$)

$$\Delta\left(\frac{I_{it}}{K_{it-1}}\right) = 0.06 \times (0.123 - 0.152 \times 1.543) = 0.06 \times (-0.112) = -0.0067 \tag{A.8}$$

$$\Delta I_{it} = -0.0067 \times 439 = -\$2.9 \text{ million} \tag{A.9}$$

Very High Investment Opportunities (90th percentile, $Q = 2.945$)

$$\Delta\left(\frac{I_{it}}{K_{it-1}}\right) = 0.06 \times (0.123 - 0.152 \times 2.945) = 0.06 \times (-0.325) = -0.0195 \tag{A.10}$$

$$\Delta I_{it} = -0.0195 \times 439 = -\$8.6 \text{ million} \tag{A.11}$$

These effects represent 0.08%, -0.66%, and -1.96% of the median capital stock, respectively. The magnitudes demonstrate economically meaningful heterogeneity. Passive ownership has minimal effects for low-Q firms but substantial negative effects for high-growth firms.

The impact scales proportionally with firm size. For large firms at the 90th percentile of capital stock ($6.63 billion), the effect at high Q values reaches -$130.1 million. However, fewer than 5% of sample observations involve such extreme combinations of size and growth opportunities.

IF.2 Investment Timing and Adjustment Speed

Our model predicts that passive ownership increases adjustment frictions, leading to slower investment responses following economic shocks. We quantify this delay using the dynamic panel estimates from Table 5.

The persistence parameter λ in the autoregressive specification

$$\frac{I_{it}}{K_{it-1}} = \lambda \frac{I_{i,t-1}}{K_{i,t-2}} + (1 - \lambda)[\text{target investment rate}] + \varepsilon_{it}. \tag{A.12}$$

This increases monotonically across passive ownership terciles as, $\lambda = 0.246$ (low), $\lambda = 0.298$ (medium), and $\lambda = 0.321$ (high).

The half-life of adjustment to target investment levels is calculated as

$$h = \frac{\ln(0.5)}{\ln(\lambda)}. \tag{A.13}$$

Low passive ownership, $h = \frac{\ln(0.5)}{\ln(0.246)} = \frac{-0.693}{-1.401} = 0.49$ years = 1.97 quarters

High passive ownership, $h = \frac{\ln(0.5)}{\ln(0.321)} = \frac{-0.693}{-1.135} = 0.61$ years = 2.44 quarters

The difference in adjustment speed is $2.44 - 1.97 = 0.47$ quarters, or approximately 1.4 months. For a one standard deviation increase in passive ownership (covering 40.5% of the tercile range), the proportional delay is $0.405 \times 0.47 = 0.19$ quarters, or approximately 0.6 months.

This quantification demonstrates that the passive ownership does slow investment adjust-

ment. But the economic magnitude remains pretty modest for typical firms. The delay of less than one month probably represents a reasonable trade-off for the cost savings and stability benefits associated with passive capital. This is consistent with our matching framework's primarily efficient interpretation of the ownership.

IF.3 Aggregate Implications

The rise in value-weighted passive ownership from 3% to 14% between 2000 and 2021 affects firms controlling roughly $2.4 trillion in capital. Our estimates show that investment effects are concentrated among high-growth firms. These are important firms, but they represent a small fraction of total capital. This concentration limits the aggregate economic impact. It also serves to highlight the importance of efficient investor-firm matching for specific segments of the capital market.

IG Matching Equilibrium Definition

Our equilibrium definition is a version of the standard concept of a competitive equilibrium in a transferable utility (TU) assignment model. This is foundational in the literature on matching markets. It originates in early papers, notably Shapley and Shubik (1971) on assignment games, and Becker (1973) on marriage markets with TU. The idea is that firms and fund managers sort endogenously to maximize total surplus, with transfers. Implicitly the transfers are by ownership shares or fees. The use of shadow prices to enforce market clearing is similar to a Walrasian equilibrium. Prices adjust to balance supply and demand across heterogeneous types. The result is Pareto efficient.

This definition is reasonable for several reasons. First, in financial markets utility transfers are feasible through monetary payments or share allocations. This captures efficient sorting without frictions. It is consistent with a no-arbitrage principle. Second, it allows for analytical tractability in deriving predictions on heterogeneous effects and mismatches. This is emphasized in modern extensions (Che et al., 2024). Third, by focusing on surplus maximization, it provides a benchmark for efficiency. As a result we distinguish endogenous outcomes in our model from distortions. This is particularly important for studying passive ownership where mechanical rules like index inclusion can disrupt optimal pairings.