Technology Adoption, Market Power, and the Dual Dynamics of Value Premium and Markups*

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Abstract

We provide a unified explanation for the declining value premium and rising markups. Using firm-level data, we show that both patterns are driven by high-markup firms, while low-markup firms have stable markups and value premia. We develop a monopolistic-competition model with technology-frontier shocks and endogenous adoption, in which firms' adoption decisions respond to competitive conditions. The model shows that rising frontier efficiency, combined with heterogeneity in adoption incentives and demand elasticity, generates these dynamics. These heterogeneities distort capital allocation and slow productivity growth. We validate the mechanism with measures of technology adoption and a two-factor model with a frontier-shock proxy.

Keywords: markups; value premium; technology adoption; market power; productivity; technology frontier shocks

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1 Introduction

Recent studies document two significant economic shifts over the past decades: a persistent decline in the value premium (Fama and French, 2021) and a concurrent rise in corporate markups (De Loecker, Eeckhout, and Unger, 2020). While the former has been linked to changing dynamics in financial markets and the latter to macroeconomic changes in industry competition, the two trends have been studied in isolation. This paper bridges these seemingly unrelated phenomena by proposing a unified framework linking both trends to a common source: shifts in market structure driven by heterogeneous technology adoptions and market power.

Empirically, we document a novel fact: the decline in the value premium and the rise in markups are predominantly driven by high-markup firms. In contrast, low-markup firms have seen no change in either their value premium or markup levels. Moreover, high-markup firms experience significantly faster productivity growth than their low-markup counterparts. We develop a dynamic monopolistic competition model featuring endogenous technology adoption to explain these patterns. The model demonstrates that improvements in the efficiency of the aggregate technological frontier, coupled with heterogeneity in firms' technology adoption decisions and demand elasticity, jointly account for the decline in the value premium, the rise in markups, and their difference across firms. Furthermore, the model implies that the high marginal production costs among low-markup firms and the high market power among high-markup firms hinder capital allocation, contributing to the slowdown in aggregate productivity growth.

We begin by documenting a substantial decline in the value premium over recent decades, consistent with the existing literature. The annualized return spread between value and growth stocks falls from 5.8% in the pre-2000 period to -0.7% after 2000, and this decline is statistically significant. Over the same period, average corporate markups for publicly traded U.S. firms rise from 1.5 in 1962–2000 to 1.7 in 2001–2021. Crucially, both patterns are concentrated among high-markup firms: for this group, the value premium drops from 9.2% to -3.6%, while markups increase from 2.1 to 2.6. By contrast, low-markup firms' value premium remains stable between 5% and 7.4%, and their markups stay roughly constant at 1.2. High-markup firms are also significantly more productive than low-markup firms, and this productivity gap widens in the post-2000 period as high-markup firms experience faster productivity growth.

To investigate the economic mechanisms linking rising markups to the decline in the value premium, we develop a dynamic monopolistic competition model with three key features: (i) stochastic shifts in the aggregate technology frontier, capturing advances in cutting-edge technologies; (ii) endogenous technology adoption, where firms pay fixed costs to upgrade; and (iii) an endogenous competitive environment, in which firms' pricing, adoption, and investment

decisions respond to aggregate conditions that are themselves determined by the aggregation of firms' decisions and the market structure. In the model, firms adopt new technologies to reduce marginal production costs, reflecting the non-rival and scalable nature of technologies such as artificial intelligence, information and communication technology (ICT), cloud computing, and automation, which allow firms to expand across product lines or markets and further lower marginal costs (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023; De Ridder, 2024; Hsieh and Rossi-Hansberg, 2023). Methodologically, we characterize a Markov-perfect industry equilibrium and solve it using a Krusell–Smith-style aggregation scheme, which makes dynamic competition with many firms tractable while preserving rich heterogeneity.

We first calibrate the model to replicate the pre-2000 economy by targeting aggregate markups and financial market moments. The model delivers an aggregate markup of 1.5—closely matching historical data—and a sizable value premium of 5.1%, consistent with observed magnitudes. In the model, markups are jointly determined by firms' demand elasticity and technology adoption decisions, which shape marginal production costs. Value firms are low-productivity firms that lag the technology frontier and cannot fully catch up because adoption is costly. As a result, their future cash flows are more sensitive to changes in the aggregate technology frontier, and they are more exposed to frontier shocks than growth firms. The model also generates significant CAPM alphas for the value premium, because cross-sectional risk is driven primarily by exposure to aggregate technology-frontier shocks, whereas the market return loads on both frontier and aggregate productivity shocks; the CAPM therefore fails to capture the cross-sectional variation in book-to-market portfolios.

To study the post-2000 economy, we focus on heterogeneity over time and across high- and low-markup firms. First, we assume a significant increase in the long-run efficiency of the technology frontier relative to the pre-2000 economy. This captures broad-based advancements in technologies (e.g., AI, automation, ICT) that have reduced production costs across firms since the late 1990s. Second, we introduce heterogeneities between low- and high-markup firms in three key dimensions: (i) demand elasticity, reflecting market power; (ii) marginal production costs (governing the benefits of technology adoption) and the costs of technology adoption; and (iii) fixed operating costs. In addition, there is within-group heterogeneity in firm-specific productivity which generates dispersion in firm-level risk exposure.

To examine heterogeneity across markup groups, we calibrate the model to match key group-specific firm-level moments—average markups, adoption rates, fixed-cost-to-sales, and net-income-to-sales ratios. The calibration shows that high-markup firms have lower marginal production costs and lower firm-level demand elasticity. Lower marginal costs raise the benefits of adoption and lead these firms to adopt frontier technologies more aggressively, while less elastic demand reflects stronger market power; together, lower marginal costs and stronger

market power support higher markups and high net-income-to-sales ratios. Because most high-markup firms lie near or on the technology frontier in equilibrium, frontier shocks affect them similarly, so value and growth firms within this group have similar exposure to technology frontier shocks and generate a near-zero value premium.

By contrast, low-markup firms face higher marginal production costs and more elastic demand. Higher marginal costs dampen adoption incentives and lead to lower adoption rates, while more elastic demand implies weaker market power; together, higher marginal costs and weaker market power result in smaller markups and lower net-income-to-sales ratios. Within this group, low-productivity value firms remain further from the frontier and are more exposed to frontier shocks than growth firms, producing a sizable value premium.

To validate the model's technology adoption mechanism, we first use textual analysis of financial statements to identify firms with a high propensity to adopt new technologies and show that these firms have rising markups and virtually zero value premia, as the model predicts. We then test the model's economic mechanism using a model-implied proxy for the aggregate technology frontier shock. Because aggregate technology frontier shocks are not directly observed, we exploit the structure of the model and show that the frontier shock is highly correlated (80%) with the negative residual of aggregate production-cost growth after controlling for aggregate revenue growth, making this residual a natural proxy: lower marginal production costs correspond to a positive frontier shock. Using this proxy, we estimate a two-factor asset-pricing model with the aggregate stock market return (proxying for aggregate productivity shocks) and the frontier-shock proxy. This two-factor model explains the value premium in both the pre-2000 and post-2000 samples, with the good fit driven by increasing exposure of book-to-market portfolios to the frontier shock in the pre-2000 period and among low-markup firms after 2000, and the estimated price of risk on the frontier-shock proxy is positive, as implied by the model. Finally, model counterfactuals show that making the post-2000 frontier too efficient drives the value premium for low-markup firms close to zero but produces unrealistically high markups for both groups. In contrast, removing cross-group differences in marginal production costs and demand elasticity eliminates the observed gaps in markups and value premia, while adoption and fixed costs play only a minor role in these moments.

The same framework also sheds light on the slowdown in aggregate productivity growth (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023; De Ridder, 2024). In our model, high marginal production costs among low-markup firms and strong market power among high-markup firms jointly amplify capital misallocation.[1] In an impulse-response analysis, imposing

[1]In the baseline calibration, high-markup firms have higher measured group productivity—defined as the sales-weighted average of firm-level idiosyncratic productivity—consistent with the data and underscoring the greater impact of marginal cost differences compared to market power.

uniform (low) marginal production costs causes a positive frontier shock to raise aggregate productivity by about 1.3% relative to the baseline, whereas imposing uniform (high) market power reduces aggregate productivity by about 0.7%. These findings imply that heterogeneity in marginal costs and market power is an important force behind slow aggregate productivity growth since the early 2000s and suggest that policies that lower structural barriers for low-markup firms (e.g., subsidies for technology adoption) or curb excessive market power among high-markup firms (e.g., antitrust reforms) could mitigate misallocation and help revive productivity growth.

Literature review This paper relates to several strands of literature. The first is the growing body of work examining recent secular trends in macroeconomics and finance. De Loecker, Eeckhout, and Unger (2020) document a substantial rise in aggregate markups in recent decades. Several studies, including Aghion, Bergeaud, Boppart, Klenow, and Li (2023), Hsieh and Rossi-Hansberg (2023), and De Ridder (2024), highlight the significant role of technological change in driving this increase, while others, such as Akcigit and Ates (2021) and Olmstead-Rumsey (2022) attribute these trends to a slowdown in imitation rates and a decline in innovation efficiency, respectively. On the finance side, Fama and French (2021) document a sharp decline in the value premium over the same period, and Herskovic, Kind, and Kung (2023) propose that the value premium varies with micro-level uncertainty in the economy. While our paper shares with Aghion, Bergeaud, Boppart, Klenow, and Li (2023), Hsieh and Rossi-Hansberg (2023), and De Ridder (2024) the idea that technological change plays a central role, it differs in two important ways. First, unlike prior work studying macroeconomic and financial trends in isolation, we show—both empirically and theoretically—that these phenomena share a common source: heterogeneity in technology adoption and market power among firms. This unified account underscores the need for cross-disciplinary frameworks. Second, by jointly analyzing trends in markups and the value premium, we leverage information from markup dynamics to identify heterogeneity in asset pricing through the marginal production cost and demand elasticity channels.

Our paper contributes to the growing literature on how changes in market structure influence industry dynamics and asset prices. Corhay, Kung, and Schmid (2020) examine the relationship between product-market concentration and risk premia, while Dou, Ji, and Wu (2021, 2022) analyze how dynamic oligopolistic competition shapes firms' profitability and risk across industries using dynamic game frameworks. Cho, Grotteria, Kremens, and Kung (2025) develop a present-value decomposition of firm value that links valuation ratios to expected future output growth, markups, fixed costs and investments, and discount rates. Corhay, Li, and Tong (2022) study the asset-pricing implications of shocks to aggregate markups. Our paper differs from these studies in two key respects. Empirically, whereas the existing lit-

erature typically emphasizes cross-sectional relationships between market concentration and asset prices, we focus on the joint trends in markups and the value premium, showing that both are driven by high-markup firms and are closely linked to the broader slowdown in productivity growth. Theoretically, in contrast to work that centers on cross-industry variation, we develop a monopolistic competition model that incorporates (i) competitive price feedback within firm groups and (ii) heterogeneity in market power and technology adoption across groups. By endogenizing markup and value-premium dynamics through these channels, our framework provides a unified explanation for the evolution of markups, asset prices, and productivity across firms with differing markups.

Our paper also contributes to the literature linking technology adoption, business cycles, and asset prices. Parente and Prescott (1994), Greenwood and Yorukoglu (1997), and Cooper, Haltiwanger, and Power (1999) study how changes in the aggregate technology frontier and the adoption of new technologies shape economic growth and business cycles. Kopytov, Roussanov, and Taschereau-Dumouchel (2018) build an explicit technology-adoption model in which firms choose when to switch from an old to a new, skill-intensive technology, with adoption costs making recessions periods of accelerated technological upgrading, while Li, Tsou, and Xu (2023) link technology adoption to capital-allocation efficiency through a learning channel. Our paper differs from this earlier work in several respects. First, we focus on the economic mechanisms driving the long-run trends in the value premium, aggregate markups, and productivity—an angle largely underexplored in the existing literature. Furthermore, we model endogenous technology adoption as a distinct investment decision that governs a firm's proximity to the technology frontier and introduces a new source of risk which allows us to study the cross-sectional asset returns.

Lastly, our model connects to recent industrial-organization work on industry dynamics and competitive equilibrium. We build on the Markov-perfect-equilibrium framework of Maskin and Tirole (1988b,a) and Ericson and Pakes (1995), but depart from the traditional finite-oligopoly focus by considering a large number of monopolistically competitive firms that respond to an aggregate industry state rather than to the individual states of named rivals. This aggregate state is itself determined in equilibrium by the collective pricing, investment, and technology-adoption decisions of all firms. To address the computational challenges of dynamic industry models with many firms, we adopt macroeconomic aggregation methods in the spirit of Krusell and Smith (1998), allowing firms to base decisions on a perceived law of motion for the industry state that is validated in equilibrium.[2] This approach enables us to

[2]Our approach is related to oblivious-equilibrium methods in Weintraub, Benkard, and Van Roy (2008, 2010). As in that literature, we exploit a reduced set of aggregate state variables to make dynamic industry models tractable, but we allow the aggregate state to reflect endogenous price competition and to feed back into firms' markups and adoption incentives.

capture how dynamic competitive pressure feeds back into firms' investment and technology adoption and, in turn, generates the joint dynamics of markups and risk premia that are central to our analysis.

The paper proceeds as follows. Section 2 shows the empirical links between the trends of markups and the value premium. Section 3 develops a dynamic model of monopolistic competition with endogenous technology adoption. Section 4 quantifies how technology and market power heterogeneity drive our results. Section 5 inspects the mechanism. Section 6 explores the model implications for aggregate productivity and tests the technology adoption channel empirically. Finally, Section 7 concludes. A separate appendix with additional robustness checks and the numerical procedure is posted online.

2 Empirical findings

This section presents the main empirical findings. We begin by examining the rise of markups alongside the decline of the value premium in the aggregate economy. Next, we demonstrate that firms with higher markups experience greater increases in markups and larger declines in their value premium. In contrast, firms with low markups exhibit stable markups and value premiums throughout the whole sample period. Lastly, we show that high-markup firms experience significantly higher productivity growth than their low-markup counterparts over the same period.

We collect data from several sources. Accounting information is from Compustat. Data on stock returns and market capitalization are from CRSP. We obtain factor returns and book-to-market (BM) sorted portfolio returns from Ken French's website.[3] We download the cleaned text data of 10-K filings from Loughran-McDonald website for textual analysis in Section 6.1.[4]

2.1 The rise of markups

An important macroeconomic trend as documented in the literature is the rapid increase in the aggregate markup. Largely consistent with De Loecker, Eeckhout, and Unger (2020) and based on our model (to be presented in Section 3), we measure a firm's markup as the ratio of its sales to the cost of goods sold.[5] Figure 1 Panel A displays the aggregate markup (sales-

[3]Link to the website is https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[4]Link to the website is at: https://sraf.nd.edu/sec-edgar-data/

[5]De Loecker, Eeckhout, and Unger (2020) measure a firm's markup as the ratio of its sales to the cost of goods sold, and scaled by an estimated industry demand elasticity coefficient. Our approach is slightly different as it is directly based on the model and does not rely on the estimated demand elasticity, since the production cost is explicitly specified in our model. Nevertheless, we demonstrate that incorporating the

weighted average) in the economy from 1962 to 2021. The average markup remained around 1.45 during the 1960s and 1970s but reached 1.77 in 2021—a 25% increase from its historical low. Similar trends are observed using alternative markup measures examined in Section 2.5. To further illustrate this shift, we divide our full sample into two periods: the pre-2000 and post-2000 periods.[6] Panel A of Table 1 tests the difference in aggregate markup before and after 2000. The results indicate a significant increase in the aggregate markup across different weighting schemes. Column 1 shows that the equal-weighted aggregate markup rose from 1.61 before 2000 to 1.87 after 2000, representing a 16.1% increase. Columns 2 and 3 reveal similarly significant increases: the asset-weighted average markup grew from 1.60 to 1.93, while the sales-weighted average markup increased from 1.50 to 1.66.

2.2 The decline of the value premium

A prominent trend in recent financial markets, as documented by Fama and French (2021), is the sharp decline in the value premium. We confirm this finding in Figure 1 Panel B, which plots the 20-year rolling average value premium over time and reveals a clear declining trend.[7] Table 2 Column 1 reports the average monthly value premium in the economy, measured as the return spread between firms in the top and bottom book-to-market quintiles for the pre- and post-2000 periods. For instance, Panel A column 1 shows that the value premium is both economically large and statistically significant in the pre-2000 period, averaging 0.48% per month with a t-statistic of 2.73. In contrast, Panel B column 1 shows that the value premium becomes negative and insignificantly different from zero in the post-2000 period.

Table 2 Panel C reports the change in the value premium between the two periods. Column 1 shows that the value premium has significantly dropped by around half a percent per month (t-statistic: -1.65) in the post-2000 period. Table 2 Panel D reports the change in the value premium in terms of its CAPM alpha. As the constant in column 1 indicates, the CAPM alpha of the value premium is 0.55% per month (t-statistic: 3.18) in the pre-2000 period. However, it has declined significantly by 0.86% per month (t-statistic: -2.69), resulting in a negative CAPM alpha in the post-2000 period. In the Online Appendix, we report similar results using alternative measures of the value premium, including the decile spread, the HML factor, and the intra-industry value premium.

estimated demand elasticity coefficient into the markup calculation does not alter our empirical findings since their measure and ours are highly correlated, as shown in Tables A.5 and A.6 of the Online Appendix.

[6]We label the pre-2000 period as from 1963 to 2000 and the post-2000 period as from 2001 to 2021. In the Online Appendix, we check the robustness of alternative cutoff periods.

[7]We identify value and growth stocks as stocks in the top and bottom book-to-market quintiles. The value premium data (i.e., quintile spread returns) are obtained from Ken French's website.

2.3 Linking the two trends

Is the decline of the value premium associated with the rise in markups? We find supporting evidence that both trends are concentrated among high-markup firms, while the value premium and markups of low-markup firms remain stable.

We start by showing that the rise in markups is not uniform across all firms. High-markup firms are the primary drivers of this increase, as their markups have grown significantly faster than those of other firms. Figure 2 Panel A provides a time series plot of the average markups for low-markup and high-markup firms from 1962 to 2021, where low- and high-markup firms are defined as those in the bottom and top markup terciles.[8] While the average markup for low-markup firms remains flat throughout the sample period, the markup for high-markup firms exhibits a noticeable and steady increase. We report the change in average markup of low- and high-markup firms in Panel B of Table 1. In this panel, we compute the sales-weighted average markup for each group. Column 1 shows that the average markup of firms in the bottom group remains stable over time. Column 2 reveals that high-markup firms see a substantial rise, with their average markup increasing by 0.54 from 2.10 before 2000 to 2.64 after 2000, representing a 26% increase.[9] Column 3 shows that the difference in markup between the low- and high-markup firms has widened significantly.

Second, we examine how the value premium varies across firms with different levels of markups, further exploring the link between markups and asset pricing patterns. Specifically, we independently sort stocks into terciles by markup and into quintiles by book-to-market ratio. This results in 15 distinct portfolios.[10] We then compute the value premium within each markup tercile as the difference in returns between value and growth stocks in that group.[11]

Figure 2 Panel B plots the rolling-average value premium for low- and high-markup firms over time. The value premium remains stable among low-markup firms, while high-markup firms exhibit a clear decline. Table 2 also provides the detailed value premium of low- and high-markup terciles. In the pre-2000 period, Panel A shows that the monthly value premia for

[8] We sort firms into three terciles based on their markups each year using NYSE cutoffs. Firms in the top tercile are high-markup firms and in the bottom tercile are low-markup firms. Although we sort firms every year, the composition of firms in each group is persistent, for example, the turnover of firms in the high-markup tercile is less than 10% per year.

[9] The average markup of firms in the middle-markup group also increased significantly, rising from 1.41 before 2000 to 1.51 after 2000.

[10] The cross-sectional correlation between markup and book-to-market ratio is low, at -14%, as shown in Table A.1. Therefore, the number of stocks in each of the 15 portfolios is reasonably large, i.e., over 100 stocks on average.

[11] Following the standard asset pricing approach, the returns of a portfolio are computed from July of the year after sorting.

low- and high-markup firms are 0.42% and 0.77%, respectively—both statistically significant.[12] The difference between the two groups is not statistically significant, indicating a robust value premium across markup levels before 2000.

In contrast, Panel B shows that in the post-2000 period, a significantly positive value premium persists only among low-markup firms, averaging 0.62% per month (t-statistic: 1.92). The value premium among high-markup firms turns negative and statistically insignificant. The difference between the two groups is -0.92% per month (t-statistic: -2.83). Panel C reports the change in the value premium within each markup group. The change for the low-markup tercile is small and insignificant, while the high-markup group experiences a sharp and significant decline of -1.07% (t-statistic: -2.76). The difference in the change between the two groups is -1.27% and statistically significant. In Panel D, we control for the market factor and present the change in the CAPM alpha of the value premium across different markup groups. As shown by the constants, the pre-2000 CAPM alphas of the value premium of low- and high-markup firms are 0.53% and 0.77% per month, respectively, with no statistically significant difference. Similar to Panel C, Panel D indicates a substantial and statistically significant decline in the CAPM alpha among high-markup firms in the post-2000 period—more than 1% per month—while the decline for low-markup firms remains statistically insignificant.

2.4 Productivity disparities across firms with different markups

Complementing the divergent trends in markups and value premiums between low- and high-markup firms, we also identify a growing divergence in their productivity trajectories: in the post-2000 period, high-markup firms exhibit substantially faster productivity growth than low-markup firms. Productivity is measured using the methodology of İmrohoroğlu and Tüzel (2014).[13] Figure 2 Panel C displays the evolution of the average productivity for low- and high-markup firms over our sample period. Throughout, high-markup firms maintain a higher productivity level than their low-markup counterparts. Moreover, this gap in productivity widens substantially in the post-2000 era, reflecting divergent growth dynamics between the two groups. In the pre-2000 period, high-markup firms achieved an average annual productivity growth rate of 0.78%, compared to 0.53% for low-markup firms. After 2000, however, high-markup firms accelerate to 0.92% per year, while low-markup firms' growth rate falls to just 0.07%. This growing productivity gap between high- and low-markup firms provides a third piece of the puzzle, suggesting that the divergent trends in markups and

[12] The returns for all 15 portfolios are reported in Table A.3 in the Online Appendix.

[13] İmrohoroğlu and Tüzel (2014) estimate firm productivity each year using an expanding-window approach (i.e., employing information up to that year). To mitigate parameter uncertainty, we instead estimate productivity over the full sample. In both cases, high-markup firms exhibit higher productivity, and the productivity gap between low- and high-markup firms remains robust to the expanding-window estimation.

the value premium are linked to, and may in part reflect, fundamental differences in firms' technological capabilities.

2.5 Robustness checks

To check the robustness of our main findings, we conduct an extensive series of robustness checks. For brevity, the complete results are presented in the Online Appendix, while we provide a brief summary of the key findings here.

Cross-sectional correlation between markup and other characteristics How correlated is markup with other firm-level characteristics? We first empirically examine the correlation structure among various variables in the data. This exercise provides us with a baseline understanding of the joint distribution of various sorting variables. Appendix Table A.1 shows that markup has a low correlation with other characteristics, such as size (9%) and book-to-market ratio (-14%). Therefore, markup is not a proxy for firm size or valuation. Appendix Table A.1 also shows that the cross-sectional correlations in the pre- and post-2000 periods are relatively similar. Therefore, there does not seem to be a structural break in the joint distribution of markup and other variables.

Alternative sample periods We examine whether the decline in the value premium depends on the choice of sample period cutoffs. In the Appendix, Table A.2 shows that the average return of the value-minus-growth quintile portfolio is 0.01% per month from 1993 to 2021, and -0.4% per month from 2011 to 2021, with neither result being statistically significant. Additionally, excluding the COVID-19 pandemic period, we find that the value-minus-growth quintile portfolio return is 0.01% per month from 2001 to 2019.[14] Similar patterns are observed for other measures of the value strategy. These findings demonstrate that the value premium has been persistently low in recent decades.

Industry-level analysis We examine industry-level markup trends and value premium trends. We sort industries into terciles based on their markups and find that industries in the top markup tercile see their average markups rise by over 10 percent in the post-2000 period, whereas those in the bottom tercile exhibit no significant change between the pre- and post-2000 eras. Similar to the firm-level findings, the value premium of industries in the lowest markup tercile remains stable throughout the entire sample period, while the value premium of industries in the top markup tercile becomes statistically insignificant after 2000. These results are presented in Table A.4 of the Online Appendix.

Alternative markup measures We also check the robustness of our results using alternative measures of markup. First, we follow the methodology of De Loecker, Eeckhout, and Unger

[14] In fact, we find that from 1984 onward, the value premium (measured as the quintile spread) was never statistically significant during any consecutive 30-year period.

(2020) to measure markup. The difference between their measure and ours is that their measure multiplies the ratio between sales and cost of goods sold by an estimated industry demand elasticity coefficient. We demonstrate that our results are robust to using their measure. Additionally, we consider another alternative definition of the markup. In this definition, we include part of the Selling, General, and Administrative (SG&A) expenses in the variable cost, since the SG&A expense might not be entirely fixed. Our main findings are robust to the use of this alternative markup measure. The results of these exercises are shown in the Online Appendix Tables A.5 and A.6.

Excluding micro-cap or superstar firms We also assess the robustness of our findings by excluding micro-cap stocks. Table A.7 Panel A shows that our findings on the cross-sectional decline of the value premium remain the same when we limit our attention to non-micro-cap stocks. Autor, Dorn, Katz, Patterson, and Van Reenen (2020) document the rise of superstar firms and their impact on the aggregate labor share. We find that the markup has risen significantly among both superstar firms and non-superstar firms, as shown in Figure A.2 and Table A.8. In addition, our main findings on the cross-sectional changes in markups are similar among superstar and non-superstar firms.

Alternative explanations We also analyze several alternative explanations for the decline of the value premium and the rise of markups. The Online Appendix reports these results, including: the size effect (Section A.4); the rise of superstar firms (Section A.5); fluctuations in micro-uncertainty (Section A.7); the role of other firm characteristics, including evidence that controlling for intangible assets does not overturn the decline in the value premium (Section A.8); the impact of new entries (Section A.9); and the relationship between the value premium and interest rates (Section A.10). Overall, none of these alternative channels accounts for the decline in the value premium.

3 Model

In this section, we present a dynamic monopolistic competitive equilibrium model with aggregate productivity shocks and technology frontier shocks to understand the empirical findings and perform counterfactual analyses.

3.1 Setup

The model features a stochastic technology frontier, costly technology adoption, and an endogenous competitive environment in which firms' pricing and adoption decisions respond to aggregate competitive conditions. We allow for several sources of heterogeneity: (i) over time, in the efficiency of the aggregate technology frontier; (ii) across groups, including differences

between low- and high-markup firms in the benefits (marginal production costs) and costs of frontier technology adoption, firm demand elasticity, and fixed operating costs; and (iii) within groups, in firm-specific productivity.

The time-series heterogeneity captures the fact that aggregate technology has advanced substantially since the late 1990s, including the widespread adoption of information technology, artificial intelligence, automation, and related innovations that have significantly improved production efficiency (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023; Hsieh and Rossi-Hansberg, 2023). Cross-group heterogeneities capture variation in the gains from lowering marginal production costs and in the costs of adopting new technologies, which can be attributed to the match between new technologies and organizational structures, as well as differences in firms' market power. Firm-specific productivity generates within-group dispersion. We discipline these cross-time and cross-group heterogeneities using both asset-pricing and quantity moments across firms and over time.

In our framework, the competitive environment is endogenous and, unlike oligopolistic models where firms respond to individual rivals, firms respond to the aggregate industry state. Competition operates through prices: as firms expand production, the aggregate price level falls, reflecting stronger competitive pressure and lower markups. These feedbacks generate dynamic equilibrium effects at the industry level. Firms take aggregate competitive conditions as given when choosing prices and technology adoption, but these conditions are themselves determined in equilibrium by the collective pricing and adoption decisions of all firms.

3.2 Demand

All firms compete in the product market and set their prices simultaneously in each period t. We assume that each firm j in the market faces a demand function $d(p_{j,t}; Q_t, P_t)$:

$$d(p_{j,t}; Q_t, P_t) = Q_t \left(\frac{p_{j,t}}{P_t} \right)^{-\xi}, \tag{1}$$

where $p_{j,t}$ is the individual firm j's output price, Q_t and P_t are the aggregate industry output and price index.[15] The parameter ξ controls the elasticity of substitution between different products, which we refer to as the firm's demand elasticity. This demand function is consistent with Dixit and Stiglitz (1977) who characterize the structure of the standard monopolistic competition model, and is widely used in the literature, e.g., Aw, Roberts, and Xu (2011), Corhay, Kung, and Schmid (2020) among others. Furthermore, we assume that the aggregate

[15]The demand function equation (1) can be derived under the economy where the industry converts the firms' intermediate goods into a final good using a constant elasticity of substitution (CES) technology.

industry output faces an isoelastic demand curve with

$$Q_t = P_t^{-\eta}, \tag{2}$$

where η is the elasticity of the industry demand. The demand elasticity of substitution across products within an industry is higher than the elasticity of substitution across industries $\xi > \eta$ (Corhay, Kung, and Schmid, 2020).

3.3 Production technology

Firms use physical capital ($k_{j,t}$) to produce a differentiated product ($y_{j,t}$). The production function exhibits constant returns to scale given by

$$y_{j,t} = X_t z_{j,t} k_{j,t}, \tag{3}$$

where X_t and $z_{j,t}$ are aggregate and firm-specific productivities. Both aggregate and firm-specific productivities (in log terms) follow an AR(1) process

$$\log(X_{t+1}) = \rho_x \log(X_t) + \sigma_x \varepsilon_{t+1}^X, \tag{4}$$

$$\log(z_{j,t+1}) = \rho_z \log(z_{j,t}) + \sigma_z \varepsilon_{j,t+1}^z, \tag{5}$$

in which ε_{t+1}^X is an i.i.d. standard normal aggregate productivity shock and $\varepsilon_{j,t+1}^z$ is an i.i.d. standard normal shock (drawn independently across firms), ρ_x and ρ_z, σ_x and σ_z are autocorrelations and conditional volatilities of aggregate and firm-specific productivities, respectively.

Taking equation (3) together, we get the firm's revenue function:

$$rev_{j,t} = p_{j,t} y_{j,t} = p_{j,t} X_t z_{j,t} k_{j,t}. \tag{6}$$

Physical capital accumulation is given by

$$k_{j,t+1} = (1 - \delta_k)\, k_{j,t} + i_{j,t}, \tag{7}$$

where $i_{j,t}$ represents investment and δ_k denotes the capital depreciation rate.

Following Abel and Eberly (1994), Cooper (2006), and Gomes and Schmid (2010), we assume that capital investment is irreversible, that is $i_{j,t} > 0$.

3.4 Technology frontier and technology adoptions

Motivated by Parente and Prescott (1994) and Parente (1995), we assume that the stock of general and scientific technology of the entire economy, denoted by S_t, evolves stochastically. This stock of technology encompasses new production technologies that generate productivity gains, including information, communication, and telecommunication (ICT) technologies, cloud storage and computing, automation, artificial intelligence, and innovative management practices that enhance firm efficiency. We assume that the stochastic technology frontier S_{t+1} follows the process below:

$$s_{t+1} = (1 - \rho_s)\,\bar{s} + \rho_s s_t + \sigma_s \varepsilon^s_{t+1}, \tag{8}$$

in which $s_{t+1} = \log(S_{t+1})$, ε^s_{t+1} is an i.i.d. standard normal shock that is independent of all the other shocks in the economy, and ρ_s and σ_s are the autocorrelation and conditional volatility of the technology-frontier process, respectively.[16] $\bar{s}$ is the long-run mean of the technology frontier.

We assume that all firms have access to the aggregate technology frontier S_t. Given the aggregate technology frontier, the aggregate and idiosyncratic productivities, firms can advance their technology level by choosing to adopt the latest technology. This choice determines their firm-specific technology capital $n_{j,t}$, which directly increases production efficiency by reducing the marginal production costs.

If firms choose to adopt the frontier technology, their technology capital is upgraded to S_t. Conversely, if firms choose not to adopt, their technology capital depreciates at the rate of δ_n. Let $\phi_{j,t} = 1$ denote adoption and $\phi_{j,t} = 0$ denote not adoption. The evolution of firms' technology capital $n_{j,t}$ can be described as the following:

$$n_{j,t} = \begin{cases} S_t, & \text{if } \phi_{j,t} = 1 \\ (1 - \delta_n) n_{j,t-1}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{9}$$

Accordingly, firms' technology capital investment $h_{j,t}$ follows

$$h_{j,t} = \begin{cases} S_t - (1 - \delta_n) n_{j,t-1}, & \text{if } \phi_{j,t} = 1 \\ 0, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{10}$$

The benefit of adopting the frontier technology is that firms are more efficient with lower

[16] We interpret innovations ε^s_{t+1} as shocks to frontier progress relative to its expected path. A negative shock therefore means that the frontier advances less than expected in that period, rather than implying literal destruction of existing technological knowledge.

marginal production costs. Moreover, it increases firms' continuation value, as lower production costs lead to greater capital accumulation and higher future cash flows. In modeling the firm's production costs, we follow a standard approach used in the literature on firm heterogeneity, trade, and competition (e.g., Melitz (2003); Dou, Ji, and Wu (2021)). Specifically, we assume that a firm's variable production cost is a linear function of its output, implying a constant marginal cost for a given level of technology. This simplification preserves tractability and allows the model to focus on the key dynamic mechanisms of interest: the firm's endogenous technology adoption decision and its interaction with market power in shaping markups and risk premia. Specifically, we assume the marginal production costs for adopters are given by $\frac{f_o}{S_t}$ with $f_o > 0$ and the production costs are given by $\frac{f_o}{S_t} y_{j,t}$.

For firms that choose not to adopt, they keep operating with the old technology that depreciates over time and the production cost is $\frac{f_o}{(1-\delta_n) n_{j,t-1}} y_{j,t}$. Hence, the production cost $oc_{j,t}$ is given by

$$oc_{j,t} = \frac{f_o}{n_{j,t}} y_{j,t} = \begin{cases} \frac{f_o}{S_t} y_{j,t}, & \text{if } \phi_{j,t} = 1 \\ \frac{f_o}{(1-\delta_n) n_{j,t-1}} y_{j,t}, & \text{if } \phi_{j,t} = 0 \end{cases}, \tag{11}$$

implying that $n_{j,t}$ is the key variable that determines marginal production costs.

This assumption highlights several ways in which new technologies can enhance firm efficiency by reducing production costs. First, the IT boom from 1995 to 2005 enabled firms to expand into multiple product lines. For example, advancements in cloud storage and computing helped reduce overhead costs associated with entering multiple markets (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023). Second, new technologies, particularly software, lower the marginal costs of production due to their non-rival and scalable nature, allowing firms to scale up production without additional costs (De Ridder, 2024). Furthermore, ICT technology and innovative management practices have enabled firms to expand into multiple locations at a lower cost, a trend prevalent in many sectors such as services, retail, and wholesale (Hsieh and Rossi-Hansberg, 2023).

Technology adoption is costly. To adopt the latest frontier technology S_t, firms must incur a fixed operating cost denoted by f_a. Therefore, the adoption costs $ac_{j,t}$ are as follows:

$$ac_{j,t} = \begin{cases} f_a, & \text{if } \phi_{j,t} = 1 \\ 0, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{12}$$

3.5 Firms' maximization problem

Finally, firms' dividend $div_{j,t}$ is given by

$$div_{j,t} = rev_{j,t} - oc_{j,t} - i_{j,t} - h_{j,t} - ac_{j,t} - f. \tag{13}$$

where f is the fixed operating costs.

We specify the stochastic discount factor $M_{t,t+1}$ as a function of the two aggregate shocks in the economy:

$$M_{t,t+1} = \exp(-r_f) \frac{\exp(-\gamma_x \triangle x_{t+1} - \gamma_s \triangle s_{t+1})}{E_t[\exp(-\gamma_x \triangle x_{t+1} - \gamma_s \triangle s_{t+1})]} \tag{14}$$

where $x_t = \log(X_t)$, r_f is the (log) risk-free rate, $\gamma_x > 0$ and $\gamma_s > 0$ are the loadings of the stochastic discount factor on the two aggregate shocks. The risk factor loading parameters (γ_x and γ_s) are positive. The assumption $\gamma_x > 0$ is standard in equilibrium models (e.g., Jermann (1998)): low aggregate productivity states imply low output and consumption and thus high marginal utility. The assumption $\gamma_s > 0$ is consistent with evidence that consumption rises after technology-frontier shocks (Baron and Schmidt, 2014) and during major frontier-growth eras such as Electrification and IT (Jovanovic and Rousseau, 2005). Given the SDF, expected excess returns are priced by covariances with aggregate productivity and technology-frontier shocks; in our quantitative analysis, differences in exposure to the frontier shock are the main source of cross-sectional variation in expected returns. We assume a constant risk-free rate to focus on risk premia as the main driver of our results and to avoid unnecessary parameter proliferation.

We denote the vector of state variables as $\Theta_t = \left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$. It includes (1) a firm's capital stock, $k_{j,t}$, (2) a firm's technology capital $n_{j,t-1}$, (3) the firm's idiosyncratic productivity, $z_{j,t}$, (4) aggregate productivity, X_t, (5) the current value of aggregate technology frontier, S_t, (6) the joint distribution of idiosyncratic productivity, and firm-level capital stocks and technological capital, χ_t, which is defined for the space U=$\mathrm{R}_+ \times \mathrm{R}_+ \times \mathrm{R}_+$.

We denote firms' value function by $v_{j,t}(\Theta_t)$ as the cum-dividend market value of the firm in period t. Firms solve the maximization problem by choosing price $p_{j,t}$, capital investment $i_{j,t}$ and adoption $\phi_{j,t}$ decisions optimally:

$$v_{j,t}(\Theta_t) = \max_{p_{j,t}, i_{j,t}, \phi_{j,t}} : \left\{ div_{j,t} + E_t\left[M_{t,t+1} v_{j,t+1}(\Theta_{t+1})\right] \right\}, \tag{15}$$

subject to the demand–capacity constraint

$$d(p_{j,t}; Q_t, P_t) \geq y_{j,t} = X_t z_{j,t} k_{j,t}, \tag{16}$$

the capital accumulation equation (7) and the flow of funds constraint (13) for all dates t given a law of motion for the joint distribution of idiosyncratic productivity, physical capital, and technology capital

$$\chi_{t+1} = \Gamma\left(X_t, S_t, \chi_t\right) \tag{17}$$

3.6 Equilibrium markups and optimal technology adoptions

To derive the model-implied markup, we first obtain the firm's optimal price decision and then the implied time-varying markup (price–marginal-cost ratio) in Proposition 1. We also analyze the optimal technology adoption decision in Proposition 2.

Proposition 1. *Let demand and aggregation follow equations (1)–(2), production and productivity follow equations (3)–(5), and dividends follow equation (13). In the optimal pricing problem, with predetermined capital, the demand–capacity constraint $d(p_{j,t}; Q_t, P_t) \geq y_{j,t}$ binds, and the firm therefore chooses the unique price that equates demand to capacity:*

$$Q_t\left(\frac{p_{j,t}}{P_t}\right)^{-\xi} = y_{j,t} \quad \Longrightarrow \quad p_{j,t} = P_t^{1-\eta/\xi}\left(X_t z_{j,t} k_{j,t}\right)^{-1/\xi}. \tag{18}$$

Defining the firm's markup as the ratio of price to marginal cost, the model-implied markup ($\mu_{j,t}$) is

$$\mu_{j,t} = \frac{rev_{j,t}}{oc_{j,t}} = \begin{cases} P_t^{1-\eta/\xi}\left(X_t z_{j,t} k_{j,t}\right)^{-1/\xi} \frac{S_t}{f_o}, & \text{if } \phi_{j,t} = 1, \\ P_t^{1-\eta/\xi}\left(X_t z_{j,t} k_{j,t}\right)^{-1/\xi} \frac{(1-\delta_n) n_{j,t-1}}{f_o}, & \text{if } \phi_{j,t} = 0. \end{cases} \tag{19}$$

Proof. See details in Appendix C.1.

Intuitively, the maximization over $p_{j,t}$ is a static problem that separates from the intertemporal choices $(\phi_{j,t}, i_{j,t})$. Given predetermined capacity $y_{j,t}$, the firm chooses $p_{j,t}$ to clear the demand-capacity constraint.

$$v_{j,t}(\Theta_t) = \max_{\phi_{j,t}\in\{0,1\},\, i_{j,t}} \Big\{ \underbrace{\max_{p_{j,t}>0} \; p_{j,t} y_{j,t} - oc_{j,t}}_{\text{subject to } d(p_{j,t};Q_t,P_t)\geq y_{j,t}} - i_{j,t} - h_{j,t} - ac_{j,t} - f + \mathbb{E}_t[M_{t,t+1}\, v_{j,t+1}(\Theta_{j,t+1})] \Big\}.$$

Binding demand implies $Q_t\left(\frac{p_{j,t}}{P_t}\right)^{-\xi} = y_{j,t}$, so the optimal price $p_{j,t}$ depends only on aggregate conditions (P_t, Q_t) and the firm's realized capacity $(X_t z_{j,t} k_{j,t})$, not on its technology capital $n_{j,t}$. If the constraint were slack, a small increase in price would raise revenue while remaining feasible, so optimality requires pricing at the point where demand exactly equals capacity. Because capacity $y_{j,t}$ is predetermined, the firm's price choice is a static problem:

it sets $p_{j,t}$ to satisfy the demand–capacity constraint but does not adjust price in response to firm-specific technology choices. We refer to this as capacity-constrained pricing.

Unlike standard models with price rigidities (e.g., Calvo pricing), where firms cannot freely reset prices, here prices are fully flexible each period but constrained by predetermined capacity within the period. In a standard unconstrained setting, a drop in marginal cost would induce a proportional drop in price, preserving a constant markup. Here, however, the optimal price is decoupled from marginal cost: it is pinned down by fixed supply and cannot adjust downward to reflect contemporaneous efficiency gains. Consequently, reductions in marginal cost caused by technology adoption show up as changes in markups rather than lower prices. This capacity-constrained pricing rule is a natural device in our setting, where the key friction is slow adjustment of technology and capacity rather than price stickiness. It keeps the firm problem tractable while delivering state-dependent, time-varying markups tightly linked to firms' adoption choices. Alternative approaches to time-varying markups in the literature typically rely on nominal rigidities or strategic pricing in finite oligopolies; our mechanism is complementary to these and tailored to the technology-adoption channel we emphasize.

Total production costs consist of production costs $oc_{j,t}$, adoption costs $ac_{j,t}$, and fixed operating costs f. Since $ac_{j,t}$ and f do not vary with output,[17] and production costs are linear in $y_{j,t}$, marginal cost is $MC_{j,t} = \frac{\partial oc_{j,t}}{\partial y_{j,t}}$. The firm's markup, defined as price over marginal cost, is therefore $\mu_{j,t} = \frac{p_{j,t}}{MC_{j,t}} = \frac{rev_{j,t}}{oc_{j,t}}$, which yields the expression in Equation (19).

In contrast to the optimal price, the marginal cost depends directly on $n_{j,t}$, so firms that adopt frontier technology have strictly higher markups whenever $S_t > (1-\delta_n)n_{j,t-1}$, reflecting lower marginal production costs. It is helpful to relate our model to the existing literature on equilibrium markups. While our environment features monopolistic competition, it departs from standard frameworks (e.g., Dixit and Stiglitz (1977)) that typically imply constant markups: here, predetermined capacity generates capacity-driven price constraints, so technology adoption affects marginal costs but not prices. This mechanism produces endogenous markup dispersion and helps the model match the cross-sectional patterns observed in the data.

Prior studies estimate markups either from optimal pricing (consumer-side) or from inferred marginal costs using a constrained cost-minimization problem (production-side), as in De Loecker, Eeckhout, and Unger (2020). Our model's markup measure, the ratio of total sales to variable production costs, is closer to the production approach but avoids the need to estimate output elasticities because variable costs are linear in output (as in Melitz (2003);

[17] It is worth noting that $ac_{j,t}$ is not differentiable everywhere—specifically, at the discrete moments when firms switch between adoption and non-adoption states. However, in our discrete-time setting, these switching points do not correspond to cash flow realizations and thus do not affect equilibrium outcomes. As a result, they have no bearing on the computation of markups, which are defined based on realized flows within each period.

Dou, Ji, and Wu (2021)). This structure delivers a transparent expression for marginal costs and a markup measure that maps directly into firms' technology adoption and market power, which in turn underlie the risk premia we study.

We now characterize optimal technology adoption. In contrast to the static pricing problem, adoption is an intertemporal decision that trades off current and future benefits.

Proposition 2. *For $i \in \{adopt, noadopt\}$, let $div^i_{j,t}$ denote firm j's optimal current dividend at date t under adoption decision i, and let $v^i_{j,t+1}$ be the corresponding ex–dividend firm value at date $t+1$. Then firm j adopts the frontier technology at date t (i.e., chooses $\phi_{j,t} = 1$) if and only if*

$$\underbrace{\left(div^{adopt}_{j,t} - div^{noadopt}_{j,t}\right)}_{\text{current dividend gain}} + \underbrace{\mathbb{E}_t\left[M_{t,t+1}\left(v^{adopt}_{j,t+1} - v^{noadopt}_{j,t+1}\right)\right]}_{\text{continuation value gain}} \geq 0. \tag{20}$$

Proof. See details in Appendix C.2.

Intuitively, a firm adopts when the sum of two terms in equation (20) is non-negative. The first term is the current dividend gain, which mainly reflects the reduction in variable production costs $\left(\frac{f_o}{(1-\delta_n)n_{j,t-1}} - \frac{f_o}{S_t}\right) y_{j,t}$, when the firm moves from depreciated technology to the frontier. The second term is the discounted continuation-value gain: by adopting now, the firm benefits from lower marginal costs and higher cash flows in all future periods, as summarized by the difference in continuation values. Adoption is therefore driven both by contemporaneous efficiency gains and by the present value of future benefits from operating at the technology frontier.

3.7 Equilibrium characterization

Lastly, we characterize the equilibrium and discuss the equilibrium approximation approach.

3.7.1 Monopolistic competitive equilibrium

Monopolistic competitive equilibrium implies that firms take into account the decisions of all other competitors when determining their optimal choices. Building on the foundational work of Maskin and Tirole (1988a) and Ericson and Pakes (1995), we focus on the Markov Perfect Equilibrium such that the optimal decisions of firms depend on the current states that affect their payoff functions. A Markov-perfect equilibrium is defined as a collection of policy functions and a perceived law of motion for the aggregate state such that:

- Given the perceived law of motion, each firm chooses policy functions $p_{j,t}(\Theta_t)$, $i_{j,t}(\Theta_t)$, and $\phi_{j,t}(\Theta_t)$ that solve its dynamic programming problem, where Θ_t collects the firm-specific states and the aggregate states that affect payoffs.

- The perceived law of motion for the aggregate state coincides with the law of motion implied by aggregating firms' optimal policies.
- Goods and asset markets clear, so that aggregate quantities satisfy $Q_t = \left(\int_j y_{j,t}^{\frac{\xi-1}{\xi}} \, dj \right)^{\frac{\xi}{\xi-1}}$ and $Q_t = P_t^{-\eta}$.

3.7.2 Equilibrium approximation and endogenous competition

To analyze the dynamics of the monopolistic competition model, we compute the Markov Perfect Equilibrium using the algorithm of Krusell and Smith (1998), the standard approach for dynamic heterogeneous-agent models where the full industry state—the joint distribution of firms' capital, technology, and productivity—is intractably high-dimensional. The algorithm addresses this curse of dimensionality by summarizing the aggregate economy with a few state variables.

In our framework, the competitive environment is endogenous and, unlike in oligopolistic models where firms respond to individual rivals, firms respond only to the aggregate industry state. Competition operates through prices: as firms expand production, the aggregate price level P_t falls, reflecting stronger competitive pressure and lower markups. These feedbacks generate dynamic equilibrium effects at the industry level. Firms take aggregate competitive conditions as given when choosing prices, investment, and technology adoption, but these conditions are themselves determined in equilibrium by the collective pricing and adoption decisions of all firms.

We approximate the industry state with the aggregate capital stock $K_t = \int_j k_{j,t} \, dj$ and the law of motion for (K_t, P_t), since capital is the key endogenous driver of production and prices.[18] Firms form rational expectations about future (K_{t+1}, P_{t+1}) given current exogenous technology shocks (X_t, S_t) and the current aggregate capital stock K_t. The equilibrium is obtained by iterating until firms' perceived laws of motion for (K_{t+1}, P_{t+1}) match those generated by their collective decisions. This approach captures the endogenous feedback between firms' policies and aggregate competitive conditions while remaining computationally tractable. Details are provided in Online Appendix Section D.

This setup generates rich endogenous competition dynamics. A higher aggregate capital stock K_t lowers the aggregate price P_t as firms collectively expand capacity, with the strength of this effect governed by the industry demand elasticity η. The resulting change in P_t creates two opposing forces. First, lower expected prices reduce the marginal revenue product of

[18] Aggregate technological capital also matters in the long run, but because adoption is discrete—adopters operate on the frontier S_t while others use depreciated technologies—aggregate technological capital is already summarized by S_t.

capital, leading firms to reduce investment: when the price level is low because competition is intense, firms optimally scale back physical capital accumulation. Second, lower prices make cost-reducing technology adoption more attractive: by adopting the frontier technology, firms lower their marginal production costs and can better preserve markups in a more competitive environment. Section 4.2 analyzes these investment and adoption policies in detail.

4 Model results

This section presents the main results of the model. We first calibrate the model, then present the model-implied policy functions, and lastly discuss the results on the value premium and markups.

4.1 Calibration

To examine the joint rise in markups and decline in the value premium since around 2000, we calibrate the model separately for two distinct economies: a pre-2000 economy and a post-2000 economy. In the pre-2000 economy, we discipline parameters primarily using aggregate moments for markups, technology adoption, fixed and net income-to-sales ratios, and standard asset-pricing quantities such as the market excess return, market Sharpe ratio, and real risk-free rate.[19] In the post-2000 economy, we hold these common parameters fixed and allow a small set of technology and demand parameters to vary across low- and high-markup groups, using cross-sectional accounting moments to discipline these differences. This structure allows us to study how heterogeneity in marginal costs, adoption costs, and market power across markup groups interacts with a more advanced technology frontier to reproduce the observed patterns in markups and value premia, while limiting the scope for overfitting.

We solve the model at a quarterly frequency and report the parameters in Table 3. Because all the firm-level accounting variables in the data are only available at an annual frequency, we time-aggregate the simulated accounting data to make the model-implied moments comparable with those in the data. To generate the model's implied moments, we simulate $3,600$ firms for $1,000$ quarterly periods. We drop the first 700 quarters to neutralize the impact of the initial condition. The remaining 300 quarters of simulated data are treated as those from the economy's stationary distribution. We then simulate 200 artificial samples and report the cross-sample average results as model moments.

Parameters common across the pre- and post-2000 economies

[19] We do not incorporate heterogeneity for the pre-2000 economy because the value premium is not significantly different between low- and high-markup groups of firms over this period as shown in Table A.3.

Firm's technology. We set the industry demand elasticity $\eta = 4$ and the capital depreciation rate $\delta_k = 3.5\%$ per quarter as in Bloom (2009). Because there is no readily available depreciation rate for technology capital δ_n in the data, we set it to 4.5% (18% annually), which is within the range of empirical estimates of the depreciation rate for intangible capital in the literature.[20]

Stochastic processes. Following Jermann (1998), we set the persistence of the aggregate productivity shock $\rho_x = 0.95$ and the conditional volatility $\sigma_x = 0.01$. Given the volatility of the aggregate productivity shock, we set the persistence of the aggregate technology frontier shock to be $\rho_s = 0.95$ and the conditional volatility to be $\sigma_s = 0.02$ to match aggregate stock market volatility. To calibrate the persistence and conditional volatility of the firm-specific productivity shock, we follow Bloom (2009) and set $\rho_z = 0.95$ and $\sigma_z = 0.15$ so that the model implied cross-sectional dispersion in stock returns is 26%, close to that estimated in Campbell, Lettau, Malkiel, and Xu (2001). We calibrate the subjective discount factor $\beta = 0.995$ so that the model implied real risk-free rate is 2% per annum, close to the data moment of 2.06%. We set the loading of the stochastic discount factor on the aggregate productivity shock $\gamma_x = 4$, and the loading of the aggregate technology frontier shock $\gamma_s = 8.7$ by matching the average market excess returns and the Sharpe ratio of the market.

Parameters varying across two economies and markup groups The key parameter that varies between the pre- and post-2000 economies is the long-run average efficiency of the aggregate technology frontier ($\bar{s}$), which we calibrate following Aghion, Bergeaud, Boppart, Klenow, and Li (2023). Furthermore, we allow for heterogeneity in four key firm-level parameters between the low- and high-markup groups in the post-2000 economy: demand elasticity (ξ), marginal production cost (f_o), technology adoption cost (f_a), and fixed operating cost (f). Demand elasticity captures firms' market power, while marginal production cost (f_o) influences the benefit of technology adoption—lower f_o implies higher gains from adopting new technology given the frontier shocks. Technology adoption cost (f_a) directly affects the firm's adoption decision, and fixed operating cost (f) affects the firm's net income-to-sales ratio.

Intuitively, heterogeneity in product market power may arise from differences in product differentiation, innovation intensity, or exposure to regulatory oversight, all of which shape a firm's ability to charge prices above marginal cost. In addition, variation in marginal costs can reflect differences in how easily firms can integrate new technologies, which in turn depends on factors such as the compatibility of these technologies with existing human capital, the flexibility of organizational structures, and the availability of internal or external financing.

[20] Eisfeldt and Papanikolaou (2013) suggest that numbers between 10%-50% are all somewhat reasonable for intangible capital. Also see Li and Hall (2020) and Ewens, Peters, and Wang (2024) on estimated depreciation rates of intangible capital, including R&D capital.

Together, these heterogeneities play a central role in shaping differences in firms' markups and technology adoption outcomes across low- and high-markup groups.

We determine the four firm-level parameters by matching four key moments for each group: the average markup, the technology adoption rate (the fraction of firms adopting the frontier technology, S_t in the model, with the empirical counterpart discussed below), the fixed costs-to-sales ratio, and the net income-to-sales ratio. These moments are calibrated separately for the pre-2000 economy and for the low- and high-markup groups in the post-2000 economy. In general, the variations of the parameter values affect all moments but, to a first order, we find that the average markup helps mainly for identifying the firm's demand elasticity (ξ) and the marginal production costs (f_o); the adoption rate helps mainly for identifying the technology adoption costs (f_a), the fixed costs-to-sales ratio helps mainly for identifying the fixed operating costs (f), and the net income to sales ratio matters for identifying both the marginal production costs (f_o) and the fixed operating costs (f), and thus plays a key role in capturing firms' profitability.

Estimating technology adoption rates An important empirical input for calibrating firms' technology adoption decisions is the technology adoption rate. However, since direct estimates of this rate are unavailable in standard datasets, we construct a proxy measure using textual analysis of firms' 10-K filings. Specifically, we count the frequency of technology-related keywords (e.g., "technology," "software," "data") in these filings to identify firms that have adopted new technologies.

To calibrate our measure, we align the keyword count threshold with the average technology adoption rate for the post-2000 period. Drawing on the European Investment Bank (EIB) Investment Survey, which reports that 73% of companies in the US adopted some type of advanced digital technologies in 2022, we set a threshold of 45 keyword mentions to identify whether a firm adopts the new technology. This threshold results in approximately a 70% adoption rate in our sample in the post-2000 period.[21] For robustness, we replicate this exercise for the pre-2000 period and find an average adoption rate of 42%, consistent with lower technological penetration during this era.

Our proxy demonstrates strong validity: the keyword count correlates positively with R&D expenditure (42%), and other technology-linked investments such as intangible capital (26%) and knowledge capital (32%). These relationships suggest that our measure effectively captures the technological adoption engagement of firms. Further methodological details are provided in Online Appendix Section B.

[21]The EIB survey, covering thousands of firms in Europe and 800 U.S. firms annually, defines adoption as implementing technologies like advanced robotics, AI, or big data analytics. See https://data.eib.org/eibis/graph under "innovation activities."

4.2 Policy functions

This section examines the policy functions of the model. For the sake of brevity, we focus on the pre-2000 economy for illustration, as the qualitative patterns of the post-2000 economy remain similar. Figure 3 Panel A illustrates firms' technology adoption decisions as a function of technology capital (n), considering different levels of aggregate productivity, the aggregate technology frontier, and idiosyncratic productivity, while holding all other state variables at their long-run average values. The figure shows that firms are more likely to adopt the frontier technology when aggregate productivity (X), the technology frontier (S), or firm-specific productivity (z) is higher. This result is intuitive: higher productivity levels are associated with greater expected benefits of adoption, primarily through a higher expected marginal product of physical capital. Additionally, a more advanced technology frontier directly lowers marginal production costs, further increasing incentives for adoption. Furthermore, when a firm's current technology capital is low and far from the frontier, adoption is more likely because the benefits of upgrading outweigh the adoption cost. In contrast, firms with high technology capital, already close to the frontier, choose not to adopt, as the benefits no longer justify the adoption costs.

Recall that the aggregate capital stock K_t represents the long-run industry state that summarizes the intensity of competition in product markets. A high level of K_t is associated with a lower aggregate price P_t, reflecting stronger competitive pressure as firms expand capacity. To examine how firms' policies respond to this endogenous competitive environment, Figure 4 plots the policy functions and value functions against either firm-level physical capital k_t or technology capital n_t, varying the aggregate price level P_t.

The policy functions in Figure 4 reveal the trade-offs firms face through endogenous competition. The top-left panel illustrates the physical investment decision. As expected, a firm's investment rate is decreasing in its own capital stock, reflecting diminishing returns in the revenue function. In addition, the figure shows that investment is lower when the aggregate price level P is low—that is, when aggregate capital is high and competition is intense. Lower market prices reduce the marginal revenue product of capital, so firms optimally cut back on investment in response to a more competitive environment. As the bottom-left panel confirms, this stronger competition unambiguously erodes firm value.

The top-right panel displays the technology adoption decision. Unlike physical investment, adoption becomes more likely as P falls and competition intensifies. When aggregate prices are low, adoption of the frontier technology provides a cost advantage that helps firms sustain profits in the face of tighter competition. By lowering marginal production costs, frontier adopters can maintain higher markups than non-adopters even when prices are compressed. However, while this cost-reduction motive is strong, it does not fully offset the negative impact

of a lower price environment on revenues. Consequently, as shown in the bottom-right panel, overall firm value still declines as the competitive environment becomes tougher, even for firms that choose to adopt.

Figure 5 illustrates the model-implied markups as a function of the scaled aggregate technology frontier ($\frac{S_t}{\max S_t}$). In the pre-2000 economy, when the technology frontier is low (indicating low efficiency), firms are less likely to adopt new technology, as the cost-reduction benefits are minimal, resulting in no change in markups. However, when the technology frontier is high (indicating high efficiency), the benefits of technology adoption become significant due to greater reductions in marginal production costs. Consequently, firms choose to adopt the frontier technology, leading to an increase in markups. Comparing the pre- and post-2000 economies, firms in the low-markup group in the post-2000 economy experience lower markups. This is driven by higher marginal production costs (f_o) and lower market power, reflected in higher firm demand elasticity (ξ); the detailed calibration will be discussed in subsection 4.3. In contrast, firms in the high-markup group exhibit larger markups and higher adoption rates, benefiting from lower marginal production costs and greater market power.

4.3 Main quantitative results

This section analyzes the changes in the markup and the value premium in the model to understand the drivers of the secular trends of the two variables since 2000 in the data.

4.3.1 Pre-2000 economy

In the pre-2000 economy, we simplify the analysis by setting the mean level of the technology frontier to 1, implying $\bar{s} = 0$. We set the firm demand elasticity $\xi = 5$, marginal production costs $f_o = 0.19$, the adoption cost $f_a = 2.37$ and the fixed operating cost $f = 5.68$ so that the implied aggregate markup is 1.50, the adoption rate at 44%, the fixed costs to sales ratio at 0.17, and the net income to sales ratio at 0.05, all of which are close to the data. Notably, the model replicates observed magnitude of markups through the joint effects of firms' market power and their technology adoption decisions. It also aligns well with the main asset pricing moments, as reported in Table 4. The model-implied market return and risk-free rate are 6.20% and 2%, respectively, closely matching the data moments of 6.05% and 2.06%. The model's Sharpe ratio is 0.39, same as the observed value of 0.39.

To compute the value premium in the model, we first define the model-implied book-to-market (BM) ratio. A firm's book value of assets is its physical capital stock, $k_{j,t}$. Its market value of equity is the ex-dividend firm value, denoted by $p^F_{j,t}$, where $p^F_{j,t} = v_{j,t} - div_{j,t}$. Here, $v_{j,t}$ is the cum-dividend firm value and $div_{j,t}$ is the current dividend. We sort firms based on this model-implied BM ratio, $k_{j,t}/p^F_{j,t}$ to produce a value premium.

Importantly, the model generates a substantial value premium of 5.12%, which is close to the observed value of 5.74% in the data. In the model, value firms are those with low idiosyncratic productivity ($z_{j,t}$), outdated technology capital ($n_{j,t-1}$), and are less profitable. They generate lower current dividends and have lower expected future cash flows, resulting in a low market value ($p^F_{j,t}$) relative to their accumulated physical capital ($k_{j,t}$). These value firms lag behind the technology frontier and find it too costly to adopt new innovations. Consequently, their future cash flows are more sensitive to aggregate technology frontier shocks, making them riskier and requiring a higher expected return. In contrast, growth firms are more productive, operate at or near the technology frontier, and are therefore less exposed to these technology shocks. Moreover, the model produces a sizable spread in the CAPM alpha of 2.75% for the value premium, consistent with the failure of the CAPM in capturing the value premium in the data, although the magnitude is somewhat less than that in the data. Intuitively, the aggregate technological frontier shock drives cross-sectional risk dispersion, whereas the market return is influenced by both aggregate productivity and aggregate frontier shocks. As a result, the CAPM fails to capture the entire cross-sectional variations in book-to-market portfolios.

4.3.2 Post-2000 economy

As noted, motivated by Aghion, Bergeaud, Boppart, Klenow, and Li (2023), to capture the difference between the pre- and post-2000 economies, we assume there is an increase in the efficiency of the aggregate technology frontier ($\bar{s}$) that benefits all firms. The efficiency of the aggregate technology frontier in the post-2000 economy ($\exp(\bar{s})$) is set at 1.24, as Aghion, Bergeaud, Boppart, Klenow, and Li (2023) show that the efficiency of new technologies in 2000s reduces the overhead costs by 19.4% compared to the pre-2000 level, which implies the efficiency is $1/(1-19.4\%) = 1.24$ in the post-2000 economy.

To capture the heterogeneity between low- and high-markup groups, we calibrate the firm demand elasticity (ξ), the marginal production cost parameter (f_o), the technology adoption cost (f_a), and the fixed operating costs (f) separately for each group in the post-2000 economy. As noted, these parameters are calibrated to target key group-specific moments: the average markup, the technology adoption rate, the fixed costs-to-sales ratio, and the net income to sales ratio.

The calibration reveals substantial heterogeneities between high- and low-markup firms. High-markup firms have lower firm demand elasticity (ξ), indicating greater market power. They also incur lower marginal production costs (f_o), which implies greater benefits from technology adoption and higher production efficiency. This results in a higher likelihood of adopting the frontier technology, with an adoption rate of 81% in the model, despite higher

adoption costs (f_a). The combination of high market power and low marginal production costs yields a high markup of 2.66, closely matching the data moment of 2.63, and contributes to the increase in aggregate markup. Additionally, high-markup firms face higher fixed production costs (f), but their high operating profits lead to a higher net income-to-sales ratio. Importantly, the low marginal production costs and high market power of high-markup firms significantly reduce the dispersion of their exposure to technology frontier shocks compared to the pre-2000 economy. This reduced risk dispersion leads to a negligible value premium of 0.15%.

In contrast, low-markup firms exhibit higher demand elasticity, reflecting lower market power. In addition, low-markup firms face higher marginal production costs (f_o), which reduce the benefits of technology adoption and lower their likelihood of catching up with the technology frontier. Consequently, their markups remain low at 1.34, close to the data value of 1.2. Their net-income-to-sales ratio is also low at 0.03, consistent with the data. More importantly, due to the high operating costs and low market power among low-markup firms, their exposure to aggregate frontier shocks remains significant. As a result, the value premium for this group remains sizable at 5.34%.

Overall, this analysis highlights that heterogeneities in marginal production costs and firm demand elasticities are critical for explaining the rise in markups and the decline in the value premium. Both trends are primarily driven by high-markup firms.

5 Inspecting the mechanism

In this section, we use impulse responses and counterfactuals to examine the economic forces that drive the model's overall fit.

5.1 Impulse responses

To illustrate the economic mechanism behind the value premium, Figure 6 reports impulse responses of selected endogenous variables in the baseline pre-2000 calibration to a negative aggregate technology-frontier shock. Since firms are ex ante identical, we introduce cross-sectional heterogeneity by comparing two firms whose idiosyncratic productivity is set above and below the long-run average (labeled H and L), roughly corresponding to high- and low-market-to-book firms in the model.

The shock has asymmetric effects on firm performance. Low-productivity firms experience declines in revenue, dividends, and firm value, whereas high-productivity firms see all three rise. The key mechanism is the endogenous response of technology adoption. After the negative frontier shock, the efficiency of the technology frontier falls, so both types re-

duce their adoption rates, but the cut is less severe for high-productivity firms. As adoption slows, technology capital depreciates for both, raising marginal production costs, but this increase is much sharper for low-productivity firms because their expected adoption benefits are smaller. Their operating profits are therefore compressed more severely, leading to a large and persistent reduction in dividends.[22]

These cash-flow dynamics feed directly into valuations. The expected continuation value $E_t(v_{t+1})$ drops sharply on impact for the low-productivity firm, while it rises significantly relative to its long-run average for the high-productivity firm. As the market value of the low-productivity firm collapses while its book capital adjusts only gradually, its book-to-market (BM) ratio rises, reinforcing the identification of low-productivity firms as value firms.

These dynamics also generate cross-sectional dispersion in risk. Because current dividends represent only a small share of total firm value, returns are driven mainly by changes in expected continuation value $E_t[v_{j,t+1}]$. We summarize risk using a conditional beta with respect to the SDF, $\beta_{j,t} \equiv -\frac{\mathrm{Cov}_t\left(M_{t+1}, r^e_{j,t+1}\right)}{\mathrm{Var}_t(M_{t+1})}$, so that $E_t[r^e_{j,t+1}] = \lambda_t \beta_{j,t}$ with $\lambda_t \equiv \mathrm{Var}_t(M_{t+1})/E_t[M_{t+1}] > 0$. As shown in Figure 7, low-productivity firms have higher $\beta_{j,t}$, while high-productivity firms act as hedges. Since the stochastic discount factor (marginal utility) is decreasing in the frontier shock, which carries a positive price of risk, this difference in $\beta_{j,t}$ implies that, all else equal, low-productivity firms face substantially higher systematic risk than high-productivity firms.

Turning to the post-2000 economy, the post-2000 panels of Figure 7 show that these risk patterns differ sharply across markup groups. In the high-markup group, lower marginal production costs and less elastic demand keep both high- and low-productivity firms close to the technology frontier, so after a negative frontier shock both types hedge the shock and the dispersion in $\beta_{j,t}$ is essentially zero. By contrast, in the low-markup group, higher marginal production costs and weaker market power leave low- and high-productivity firms differentially exposed to the shock, much as in the pre-2000 economy: low-productivity firms are hit much harder, while high-productivity firms remain hedges, generating a large dispersion in risk exposure between them.

5.2 Counterfactual analysis

This section conducts the counterfactual analysis by examining the quantitative role of key features in the model, including technology frontier efficiency, firm demand elasticity, and marginal production costs, to understand the economic mechanism.

The role of cross-time heterogeneity of technology efficiency A key heterogeneity in

[22] Physical investment falls similarly for both low- and high-productivity firms due to the irreversibility constraint.

the model is time variation in frontier efficiency, $\bar{s}$. To gauge its role, we raise the incremental efficiency of the frontier in the post-2000 economy by 50% for both groups, holding cross-firm heterogeneity fixed. As shown in Table 5 (row "More efficiency increase in frontier"), the low-markup firms' markup rises to 1.38, while their value premium falls to 0.15%. The higher frontier efficiency boosts effective adoption, lowers marginal costs, and thus raises markups while compressing the value premium. For high-markup firms, the markup increases to 2.84—counterfactually high—while their value premium remains negligible because most firms in this group are already on the frontier, so the additional drop in marginal costs affects value and growth firms almost proportionally and leaves little dispersion in frontier risk.

The role of heterogeneity in firm demand elasticity In the model, firms face downward-sloping demand, with market power governed by the firm demand elasticity ξ. To assess the role of heterogeneity in market power, we set the demand elasticity of low-markup firms equal to that of high-markup firms, giving them the same market power. In this counterfactual (row "Shutting down heterogeneity in firm demand elasticity" in Table 5), the low-markup firms' markup and net-income-to-sales ratio rise from 1.34 and 0.03 to 1.60 and 0.09, while their adoption rate falls from 62% to 43%. Their value premium drops sharply from 5.34% to -0.16%. Intuitively, higher market power raises markups and operating profits, making production costs less central for future cash flows. As a result, the exposure of value versus growth firms to the frontier shock converges, and both markups and value premiums become much more similar across groups.

The role of heterogeneity in marginal production costs Another key cross-group heterogeneity is marginal production cost f_o, which governs the benefit of technology adoption. We shut this down by setting f_o for the low-markup group equal to that of the high-markup group (recall that in the baseline, low-markup firms have higher marginal costs). In this counterfactual ("Shutting down heterogeneity in marginal production costs f_o" in Table 5), the low-markup group's markup, adoption rate, and net-income-to-sales ratio jump to 2.16, 0.89, and 0.17—far above both the baseline and the data—while its value premium falls to 0. The mechanism is straightforward: lower marginal costs raise average markups and frontier adoption but make production costs less important for future cash flows, sharply reducing exposure to the frontier shock and driving the value premium to zero.

The role of heterogeneity in technology adoption costs and fixed operating costs

To assess the role of heterogeneity in adoption costs, we shut down heterogeneity in adoption costs by setting f_a for high-markup firms equal to that of low-markup firms (baseline: higher f_a for high-markup firms). As shown in the row "Shutting down heterogeneity in technology adoption costs f_a," their adoption rate rises from 0.83 to 0.90, but their markup, net-income-to-sales ratio, and value premium are unchanged, indicating that f_a mainly affects

adoption, not cash flows. Similarly, when we equalize fixed production costs f across groups (baseline: higher f for high-markup firms), the row "Shutting down heterogeneity in fixed operating costs f" shows the net-income-to-sales ratio for high-markup firms increasing from 0.09 to 0.28, while their markup, adoption rate, and value premium remain essentially unchanged, consistent with fixed costs being small relative to sales and not affecting investment or adoption decisions.

The role of price of risks We next shut down the risk prices of aggregate productivity and frontier shocks by setting γ_x and γ_s to zero in turn for both groups (rows "Zero risk price of aggregate productivity shocks" and "Zero risk price of aggregate frontier shocks" in Table 5). Both risk prices matter for the value premium, but the frontier shock is much more important: setting its risk price to zero cuts the low-markup group's value premium from 5.3% to 0, whereas setting the productivity shock's risk price to zero only lowers it to 4.51%. In contrast, neither risk price meaningfully changes markups, adoption rates, fixed-cost-to-sales ratios, or net-income-to-sales ratios, and the high-markup group's value premium is essentially unaffected because there is no risk dispersion between value and growth firms within that group.

The role of competitive price pressure In the model, firms internalize aggregate price pressure because the industry price index enters the revenue function, $rev_{j,t} = P_t^{1-\eta/\xi}(X_t z_{j,t} k_{j,t})^{1-1/\xi}$, with $1-\eta/\xi$ capturing how sensitive revenues are to aggregate prices—that is, the intensity of price competition. We weaken price competition by raising industry demand elasticity η: from 4 to 4.05 for high-markup firms (halving $1-\eta/\xi$) and from 4 to 6 for low-markup firms. As shown in the row "Weaker price competition" in Table 5, the low-markup value premium falls from 5.34% to 0.18%, while their adoption rate and net-income-to-sales ratio rise from 0.62 and 0.03 to 0.90 and 0.14. High-markup firms also see modest gains in markups, adoption, and profitability, but the effects are smaller.

Taken together, the counterfactuals in Table 5 show that only a subset of parameter changes is essential for jointly matching the post-2000 markup and value-premium patterns. Equalizing demand elasticities and marginal production costs across groups nearly eliminates the cross-sectional dispersion in markups and value premia, whereas equalizing adoption costs or fixed costs has much smaller effects on these moments. Likewise, setting the risk price of frontier shocks to zero collapses the value premium while leaving markups largely intact, whereas shutting down the productivity risk price mainly affects the aggregate market return. This pattern helps to identify the mechanism: cross-group heterogeneity in marginal costs and market power, together with a positive price of frontier-shock risk, is what drives the joint behavior of markups and value premia.

6 Model tests and aggregate implications

In this section, we conduct additional empirical tests to validate the model's mechanisms related to technology adoption and markups. We then use a model-implied proxy for the technology-frontier shock to provide further empirical support, and finally examine the implications of technology adoption for aggregate productivity.

6.1 Empirical tests of the technology adoption channel

According to our model, the rise of markup and the decline in value premium are concentrated among companies that are most likely to adopt new technologies. To test this channel more directly, we identify those firms through textual analysis by counting the appearances of technology-related keywords in a firm's annual reports.[23] We consider firms that mention these keywords most frequently in their 10-K filings as most likely to adopt new technologies.

To demonstrate how technology adoption affects markups and value premium, we sort firms into different groups each year based on the size-adjusted number of keyword appearances in their annual reports and measure each group's markup and value premium separately. Specifically, we first sort firms into two groups, large and small, based on whether their market cap is above the cross-sectional median.[24] We then sort firms within each size group into terciles based on how many times technology-related keywords appear in their annual reports. We label firms in the top and bottom terciles as high- and low-technology-adoption firms. We then measure these firms' average markup, productivity, and value premium.

Figure 8 Panel A plots the average markup of firms in the low- and high-technology adoption groups. Along with Table 6 Panel A, it shows that high-technology-adoption firms experienced the largest increase in markups—from 1.65 in 1994 to 2.22 in 2021—while low-technology-adoption firms saw little change in their markup over the same period. Table 6 Panel B reports the value premium within low- and high-technology-adoption firms during the post-2000 period. Firms in the bottom technology adoption group continue to have a sizable value premium, at 0.65% per month (t-statistic: 2.21), while the value premium of firms in the highest technology adoption group is close to zero and statistically insignificant. The difference in their value premium is -0.57% per month (t-statistic: -1.72). Additionally, Figure 8 Panel B plots the average productivity of firms in the low- and high-technology adoption

[23]The data we use for textual analysis are the cleaned 10-K files of publicly traded companies since 1994. The data are obtained from Loughran-McDonald website at: https://sraf. nd.edu/loughranmcdonald-master-dictionary. We match annual report files with financial information through cik-gvkey link table from WRDS. We define technology-related keywords as: system, sys, systems, data, software, technology, technologies, technological, and tech.

[24]Sorting firms by size first is motivated by the fact that larger companies tend to have longer annual reports, thus more likely to mention technology-related keywords.

groups. It shows that high-adoption firms have consistently higher productivity levels and faster productivity growth over the past 25 years, whereas the productivity of low-adoption firms has stagnated. Overall, these findings support the model's main channel: technology adoption plays a central role in explaining both the rise in markups and the decline of the value premium across firms.

6.2 Asset pricing tests with a technology frontier shock proxy

In this section, we use a model-implied proxy for the technology frontier shock to provide empirical support for the model's economic mechanism behind the value premium and its key assumptions. In the model, the cross-sectional difference in expected returns of the book-to-market portfolios in the pre-2000 economy and among the low-markup group in the post-2000 economy is driven by their differential exposure to the aggregate technology frontier shock, which carries a positive price of risk. Testing this mechanism and assumption in the data is challenging because there is no readily available measure of the technology frontier shock.[25] We therefore exploit the structure of the model to link the technology frontier shock to variables that can be measured in the data. This link allows us to construct a proxy for the technology frontier shock that we can use to test the model's economic mechanism in the data.

6.2.1 Construction of the technology frontier shock proxy

In the model, Δs_t denotes the change in the technology frontier that is accessible to all firms. While this concept is intuitive, it is empirically distinct from standard aggregate shocks such as TFP or market returns, making its measurement challenging. Our strategy is to aggregate firm-level observations to construct a proxy for the technology frontier shock.

Because adopting the frontier technology directly affects a firm's marginal production costs and hence the variable production cost $oc_{j,t}$ in the model, we use unexpected changes in firms' variable production costs in the data to proxy for the technology frontier shock Δs_t. Specifically, we first compute the average growth rate of cost of goods sold (COGS) for all nonfinancial firms in COMPUSTAT and denote this average as ΔC_t. Since a firm's operating cost naturally grows with its revenue, we orthogonalize the growth rate of operating costs, ΔC_t, with respect to the average growth rate of revenue in the economy, ΔL_t. To avoid look-ahead bias, we run the following regression on a rolling basis over the period 1963–2021:

$$\Delta C_t = a + b\Delta L_t + u_t. \tag{21}$$

[25] Lin, Palazzo, and Yang (2020) estimate the technology frontier using industry technology standards, but their sample ends in 2014 and is therefore not suitable for our analysis. Moreover, industry technology standards capture a broad set of technologies, whereas in our model the technology frontier specifically represents scalable technologies that reduce marginal production costs.

We then use the negative of the residuals,$-u_t$, as our proxy for the technology frontier shock and relabel it as $\tilde{s}_t \equiv -u_t$. Intuitively, a positive technology frontier shock corresponds to unexpectedly low (marginal) variable production costs (conditional on revenue growth). The details of the construction of the technology frontier shock proxy are provided in Appendix A.11.

6.2.2 Properties of the measured technology frontier shock

We provide several pieces of evidence on the validity of our constructed technology frontier shock proxy. First, within our model, we can simulate both the actual technology frontier shock, Δs_t, and the proxy based on cost residuals, $\tilde{s}_t$. The correlation between these two series in the simulated model economy is about 80%. This high correlation suggests that $\tilde{s}_t$ is a valid empirical proxy for the technology frontier shock.

Second, we examine the empirical properties of this proxy in the data. Table 7, Panel A, presents summary statistics for the technology frontier shock proxy $\tilde{s}_t$ alongside the market return. The first row reports the moments of $\tilde{s}_t$, which has a mean close to zero and a standard deviation of 1.5%. The market return is substantially more volatile, with a standard deviation of 17%.

Table 7, Panel B, shows the correlations of $\tilde{s}_t$ with the market return, utilization-adjusted total factor productivity (TFP) shocks, and several other variables related to the technology frontier. These variables include the growth in the number of technology standards (which codify and diffuse new technologies), the growth in the number of patent applications (a standard measure of innovative activity), a proxy for investment-specific technology (IST) shocks, and the revenue growth of the semiconductor industry (a key supplier of scalable general-purpose technologies).[26]

The correlation between $\tilde{s}_t$ and TFP shocks is 18%, suggesting that the frontier-shock proxy contains information that is related to, but distinct from, aggregate TFP shocks, consistent with the model's assumption. Moreover, the correlations between $\tilde{s}_t$ and measures of technology standards and related innovation activity range from 27% to 31%, indicating a moderate positive association with advances in codified technology. In addition, $\tilde{s}_t$ has a correlation of 47% with revenue growth in the semiconductor industry, consistent with the

[26]We obtain utilization-adjusted TFP from the Federal Reserve Bank of San Francisco. Motivated by Baron and Schmidt (2014) and Lin, Palazzo, and Yang (2020), we measure the annual growth in the number of technology standards issued by international organizations such as the International Organization for Standardization (ISO). Data on the number of standards come from https://www.law.northwestern.edu/research-faculty/clbe/innovationeconomics/data/technologystandards/. We also measure the annual growth rate in the number of patent applications using data from the USPTO. We measure IST shocks based on the relative price of capital goods as in Papanikolaou (2011). The semiconductor industry is identified using SIC codes 3672 and 3674.

interpretation that the frontier shock captures scalable technologies during the recent technology boom, in which microchips play a central role. Finally, the correlation between $\tilde{s}_t$ and the investment-specific technology (IST) shock is close to zero, suggesting that they capture distinct sources of variation.[27]

Taken together, these patterns indicate that our proxy captures a meaningful component of technological advances that is distinct from, yet related to, other measures of technology.

6.2.3 Technology frontier shocks and the value premium

Motivated by the two aggregate shocks in the SDF in the model, we estimate a two-factor asset-pricing model with the stock market return (proxying for the aggregate productivity shock) and the technology-frontier shock proxy as factors, in order to measure portfolios' exposure to frontier risk and its price of risk. Specifically, we use the following empirical stochastic discount factor:

$$M_t = 1 - b_M \times MKT_t - b_s \times \tilde{s}_t, \tag{22}$$

where MKT_t is the excess market return and $\tilde{s}_t$ is the technology frontier shock proxy constructed in Appendix A.11.

We estimate the coefficients on the two factors, b_M and b_s, by GMM using the standard asset pricing moment conditions $E[r^e_{it} M_t] = 0$, where r^e_{it} is the excess return on test asset i. This moment condition can be rewritten as

$$E[r^e_{it}] = \alpha_i + b_M \operatorname{Cov}(MKT_t, r^e_{it}) + b_s \operatorname{Cov}(\tilde{s}_t, r^e_{it}), \tag{23}$$

so that expected excess returns are related to covariances with the market factor and the technology frontier shock proxy. Motivated by our model, we estimate this equation separately for the pre- and post-2000 periods. As a benchmark, we also estimate the single-factor CAPM that uses only the market factor.

Table 8, Panel A, reports the CAPM and two-factor alphas (denoted by α^{CAPM} and α^{2F}) and the multivariate covariances of the book-to-market (BM) quintile portfolios. Columns 1–6 focus on the pre-2000 economy. The first row shows that, in the pre-2000 period, growth firms (column 1) have a negative CAPM alpha, while value firms (column 5) have a positive CAPM alpha. Under the two-factor model that controls for exposure to the technology frontier shock proxy, these alphas become insignificant. Looking at the covariances, growth firms have the lowest exposure to $\tilde{s}_t$, whereas value firms have the highest exposure, consistent with the

[27] In untabulated results, the frontier-shock proxy has an approximately zero correlation with interest-rate changes, indicating that it is not driven by discount-rate fluctuations.

model.

Turning to the post-2000 economy, we focus on the low-markup group, because the value premium within the high-markup group is close to zero and statistically insignificant, providing little power for our tests. Within the low-markup group, growth firms (column 7) have a negative CAPM alpha, while value firms (column 11) have a positive CAPM alpha. Moreover, growth portfolios among low-markup firms are less exposed to the technology frontier shock proxy $\tilde{s}_t$ than the value portfolios. These patterns are again in line with the model's predictions. Overall, Panel A indicates that our proxy for the technology frontier shock helps account for the value premium in both the pre- and post-2000 periods.

Table 8, Panel B, reports the estimated coefficients on the two risk factors using different sets of test assets in the pre- and post-2000 economies. In column 1, the test assets are the five BM quintile portfolios in the pre-2000 period. Column 2 adds the five investment and five operating profitability quintile portfolios to this set. Column 3 uses the five BM quintile portfolios among low-markup firms in the post-2000 period, and column 4 adds the corresponding investment and operating profitability quintile portfolios.

Across all four specifications, the estimated coefficients on the technology frontier shock proxy $\tilde{s}_t$ are significantly positive, ranging from 0.55 to 1.28, with t-statistics between 1.79 and 2.80. The MAE of the two-factor model that includes $\tilde{s}_t$ is also noticeably smaller than the MAE of the CAPM. These results provide additional empirical support for our theoretical mechanism: the technology frontier shock has a positive price of risk and helps explain the value premium.

6.3 Implications for aggregate productivity growth slowdown

It has been well-documented that total factor productivity (TFP) growth has slowed significantly over the past two decades. The literature offers several explanations for this phenomenon, including a decline in creative destruction due to rising R&D costs (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023) and an increase in entry costs for intangible-intensive firms (De Ridder, 2024), among others. Our model identifies a novel channel contributing to this slowdown: capital misallocation arising from systematic differences between low- and high-markup firms. Specifically, heterogeneity in two dimensions—marginal production costs and market power—creates inefficiencies in capital allocation, affecting aggregate productivity.

Recall that in our baseline calibration, low-markup firms face higher marginal production costs and exhibit lower market power (i.e., higher demand elasticity) than high-markup firms. Following Khan and Thomas (2013), we investigate the impact of these two frictions on measured total factor productivity (TFP), since measured TFP reflects the degree of capital

misallocation within a group and thus helps us interpret our results. Intuitively, economic frictions prevent some firms—particularly the most productive—from reaching their frictionless optimal capital levels. Consequently, less-productive firms come to hold a disproportionately large share of aggregate capital relative to their productivity, which in turn reduces measured TFP. In the baseline calibration, measured group TFP diverges in the post-2000 economy, with high-markup firms attaining significantly higher productivity.[28] This prediction is corroborated in the data: high-markup firms consistently outperform their low-markup counterparts in average measured productivity.

Moreover, as illustrated in the bottom panel of Figure 2, this gap has widened since the early 2000s in the data. The model implies that the divergence stems from two forces: (1) high marginal production costs among low-markup firms hinder efficient capital allocation, suppressing their productivity despite low market power; and (2) low marginal production costs among high-markup firms promote capital efficiency, enhancing their productivity despite strong market power. Specifically, under a counterfactual in which low-markup firms face the same (low) marginal production costs as high-markup firms, the level of measured group TFP rises by 12.6% relative to the baseline. By contrast, if low-markup firms instead share the high market power of their high-markup counterparts, their measured TFP falls by 9.8%.

Lastly, turning to the growth rate, in a simulated impulse-response analysis, Figure 9 compares aggregate TFP under each counterfactual scenario to the baseline calibration following a positive technology-frontier shock.[29] When marginal production costs are equalized at low levels, a positive technology frontier shock raises aggregate productivity to grow by 1.3% above the baseline. Conversely, when firms across markup groups share identical high market power (i.e., low demand elasticity), aggregate productivity falls by 0.7% relative to the baseline, reflecting exacerbated capital misallocation after the shock. These results underscore that the interplay of marginal production cost heterogeneity and market power disparities is a critical driver of sluggish TFP. Policy interventions aimed at reducing structural barriers—such as high marginal production costs for low-markup firms (subsidies for low-markup firms' technology adoption) and high market power among high-markup firms (antitrust reforms)—could mitigate misallocation and revitalize productivity.

[28] Measured group TFP is calculated as the sales-weighted average of firm-level productivity.

[29] We simulate the impulse responses of the baseline model and alternative models that exclude cross-group heterogeneities in firm demand elasticity and marginal production costs. Specifically, we run 500 simulations, each spanning 230 periods. In period 201, we introduce a one-time shock by increasing the aggregate technology frontier to its high level and then allow the model to evolve as before. This setup enables us to analyze the response to a one-period impulse and its gradual decay over time. To measure the impact, we compute the sales-weighted total factor productivity (TFP) for each group and then take a weighted average of them to obtain the economy-wide aggregate TFP.

7 Conclusion

We demonstrate that two seemingly unrelated secular trends—rising markups and the declining value premium—are interconnected phenomena driven by heterogeneous technology adoption and market power. Empirically, we show that these trends are concentrated among high-markup firms: their markups rise sharply over time while their value premium collapses, whereas low-markup firms exhibit stable markups and a persistent value premium. To explain these patterns, we develop a dynamic monopolistic-competition model with stochastic shocks to the aggregate technology frontier, costly technology adoption, and endogenous competition. When calibrated to the data, the model shows that improvements in frontier efficiency, together with heterogeneity in marginal production costs and market power, jointly rationalize the rise in markups, the decline in the value premium, and their divergence across firms. Critically, the model highlights how high marginal costs among low-markup firms and strong market power among high-markup firms distort capital allocation, contributing to sluggish aggregate productivity growth.

This paper bridges macroeconomic, financial, and industrial organization perspectives. For macroeconomics, we provide an industry equilibrium model linking markup dynamics and productivity trends to heterogeneity in technology adoption and market power. Embedding this heterogeneity into DSGE models will further illuminate how technology shocks and market power interact over business cycles, deepening our understanding of contemporary economic challenges. For finance, we connect the value premium's decline to shifts in firms' risk exposure driven by technology adoption. For industrial organization, we emphasize how heterogeneous technology adoption behavior within this endogenous competitive environment reinforces disparities in markups and value premia. These insights underscore the importance of studying markup and asset price trends jointly to fully grasp their interplay. Our findings have direct policy implications. Interventions aimed at reducing structural barriers—such as subsidizing technology adoption for low-markup firms and curbing anticompetitive practices among high-markup incumbents—could mitigate capital misallocation and revive productivity growth.

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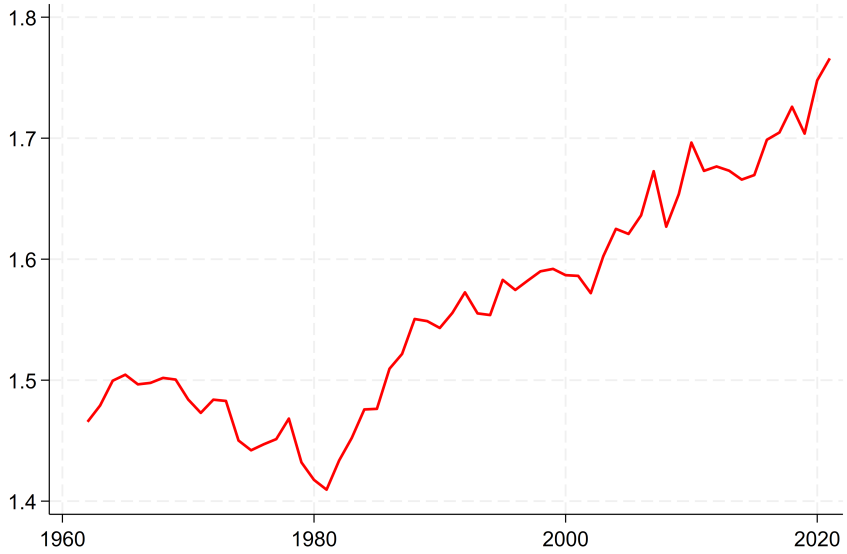
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Figure 1: Aggregate markup and value premium trends

Panel A: Aggregate markup

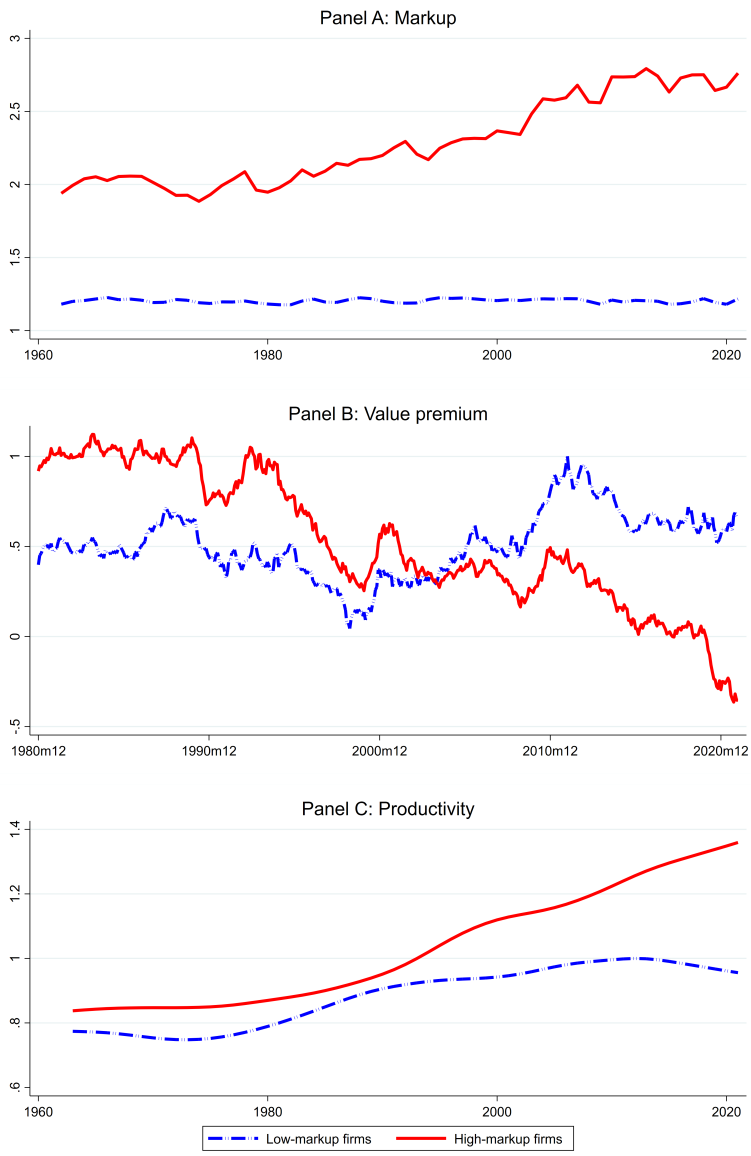


Panel B: Value premium



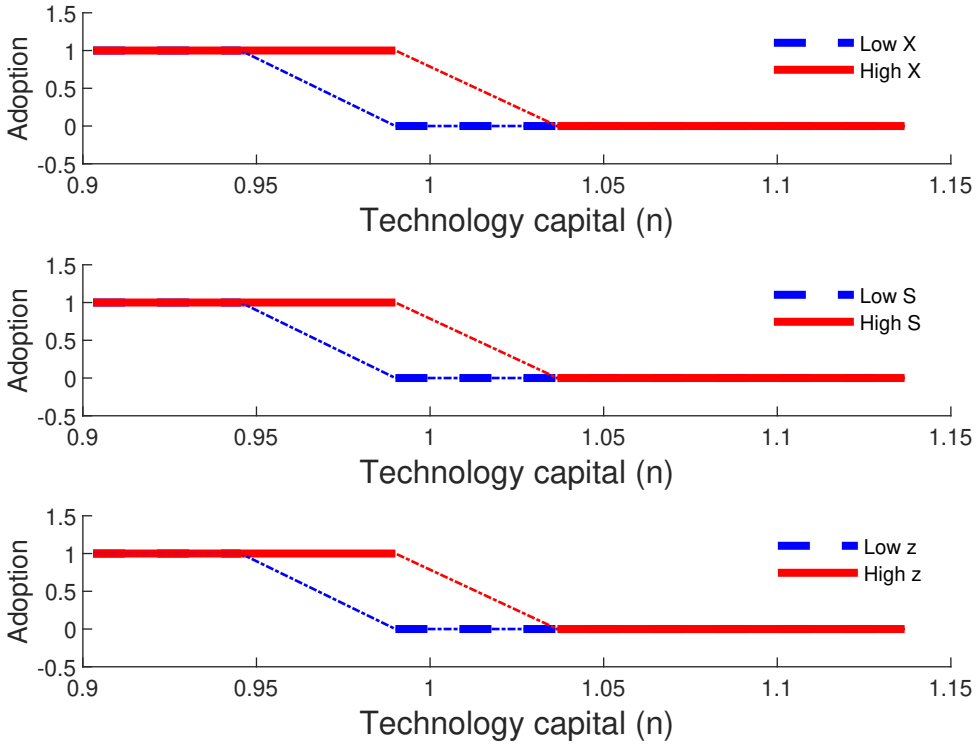
Notes: Panel A plots the aggregate (sales-weighted average) markups of US public firms, excluding utilities and financial companies. We measure a firm's markup annually as the ratio of its sales to the cost of goods sold. Panel B shows the 20-year backward rolling average of the monthly value premium, measured as the return difference between value stocks (top book-to-market quintile) and growth stocks (bottom quintile).

Figure 2: Value premium, markup & productivity of high and low-markup firms



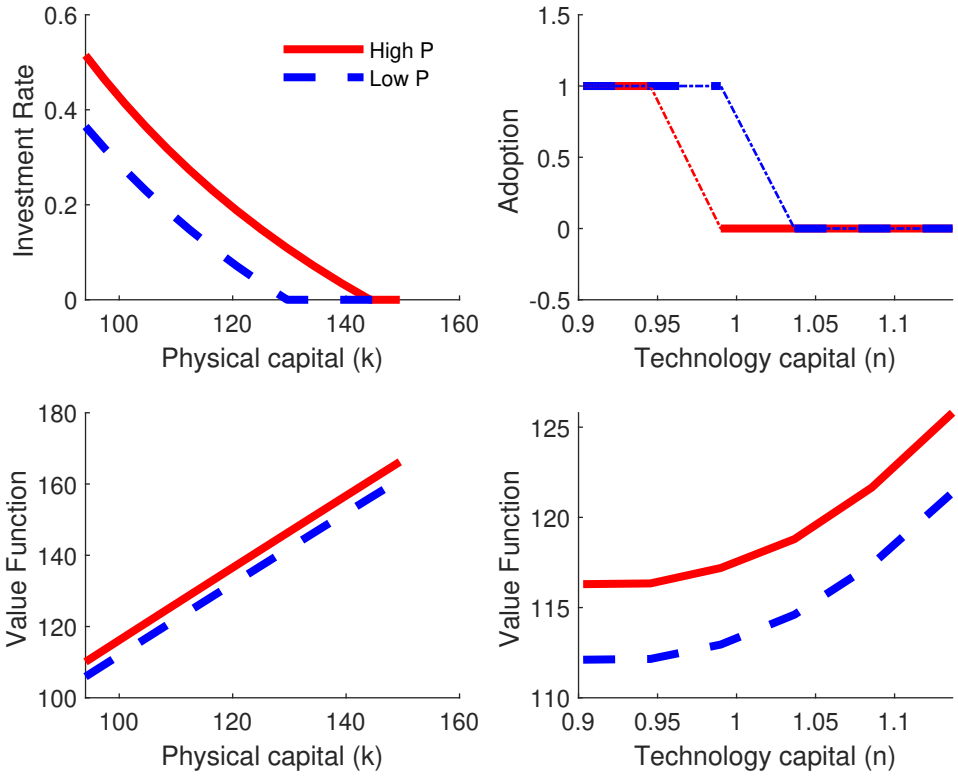
Notes: Panel A plots the sales-weighted average markup of low-markup firms (blue-dashed) and high-markup firms (red-solid). Panel B plots the 20-year (backward) rolling average value premium for high- and low-markup firms. The value premium is the return of value stocks minus that of growth stocks within each markup tercile. Low-markup (high-markup) firms are defined as those in the bottom (top) tercile of firms ranked by markup. Panel C plots the trend of sales-weighted average productivity of low- and high-markup firms. The trend is obtained using an HP filter with an annual smoothing parameter of 100. We measure productivity following the procedure outlined in İmrohoroğlu and Tüzel (2014).

Figure 3: Technology adoption policy functions



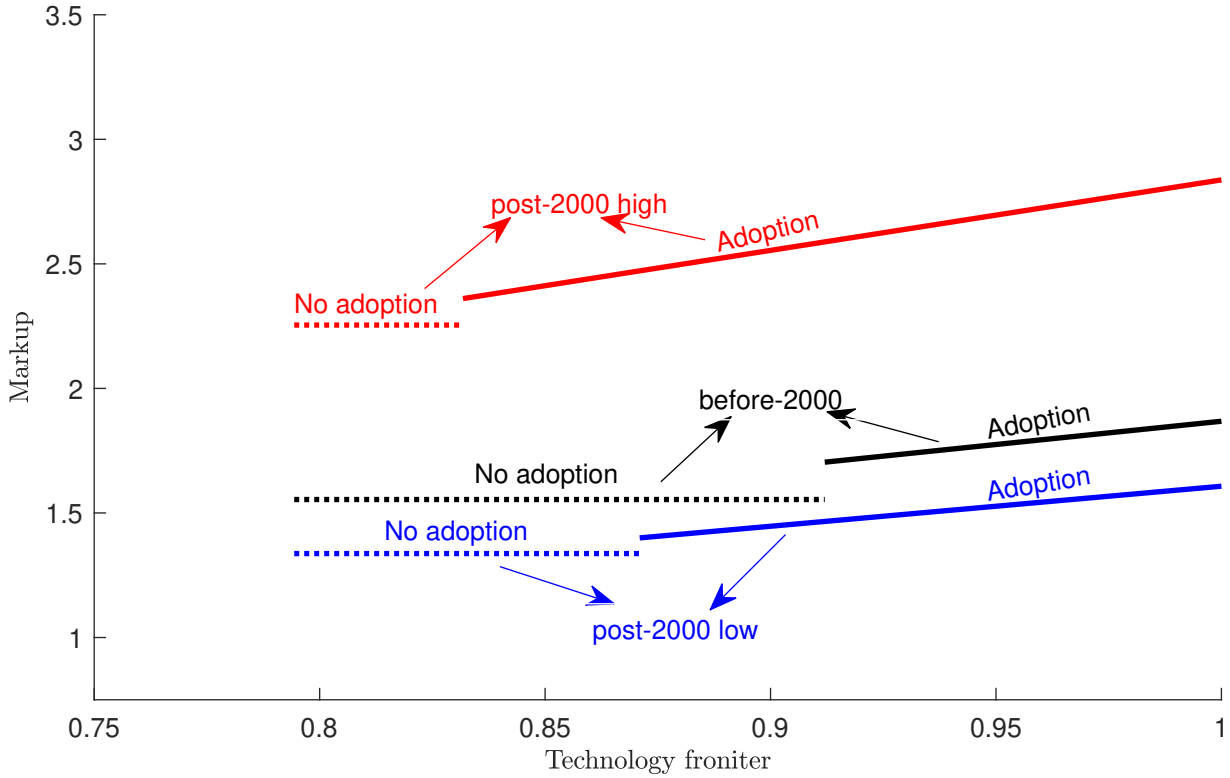
Notes: This figure plots the technology adoption decisions as a function of the technology capital (n) under the pre-2000 economy calibration. The three panels depict adoption policies with different levels of aggregate productivity X (top), technology frontier productivity S (middle), and firm-level productivity z (bottom), while all other state variables are fixed at their long-run mean values. The parameter values used in the calibration are reported in Table 3. We do not display the adoption policy functions of the post-2000 economy, as they exhibit qualitatively similar patterns.

Figure 4: Policy functions, value functions, and price competition



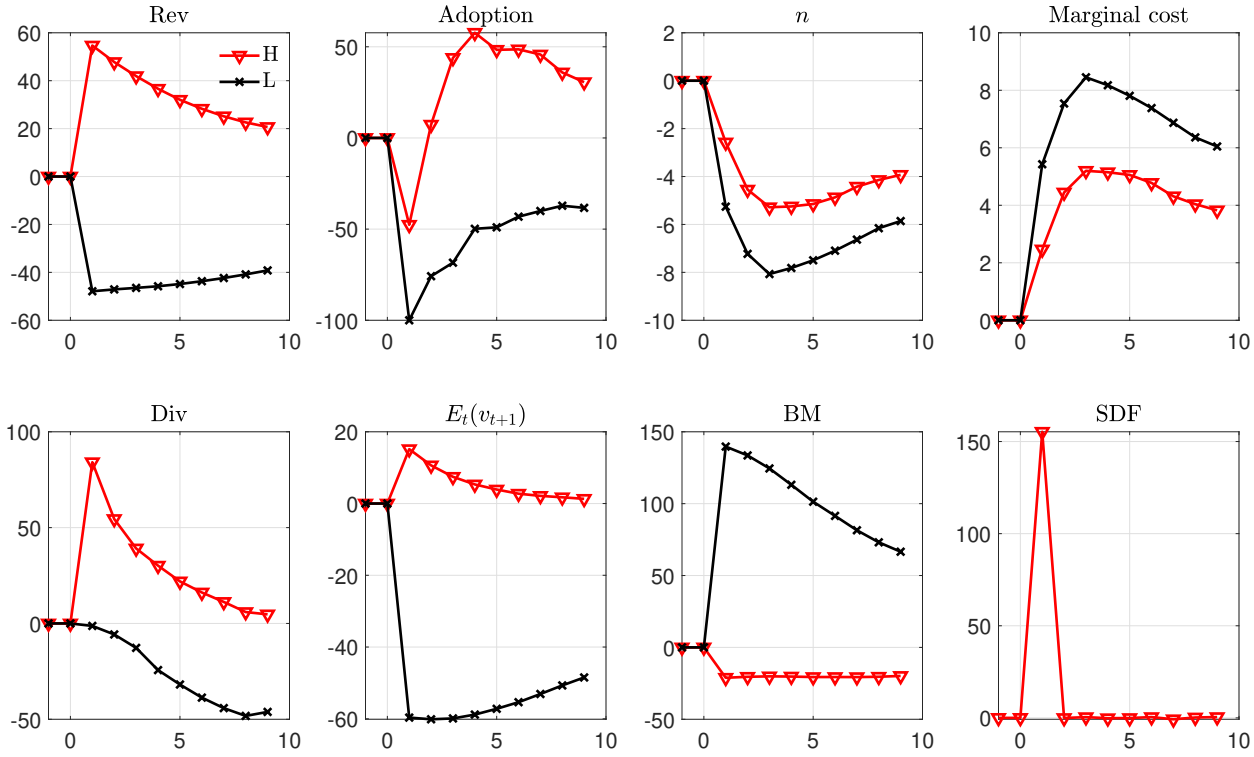
Notes: This figure plots the policy functions and value functions as functions of either physical capital (k) or technology capital (n), with different values of aggregate price P under the pre-2000 economy calibration, while other state variables are fixed at the long-run mean of the corresponding economies. The parameter values used in the calibration are provided in Table 3.

Figure 5: Model-implied markups



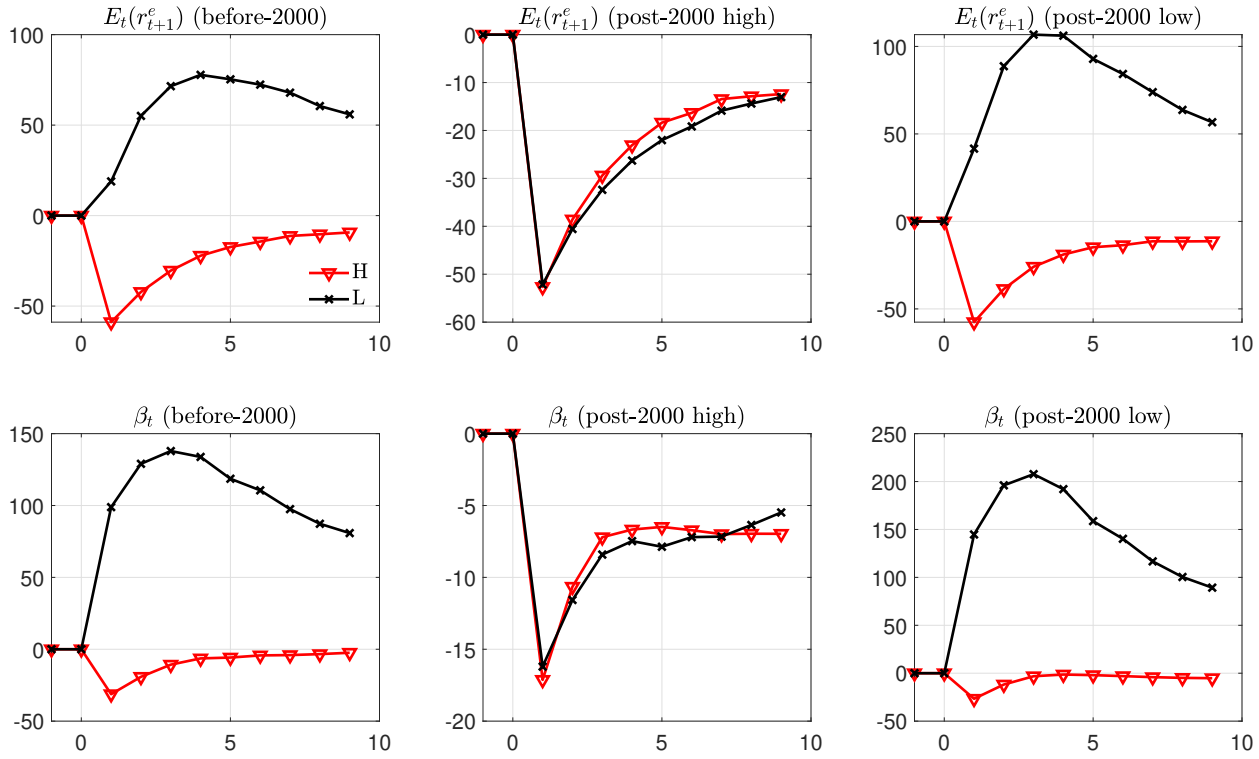
Notes: This figure plots model-implied markups as a function of the scaled technology frontier, $\frac{S_t}{\max S_t}$, under various calibrations. The black lines correspond to the pre-2000 economy, while the blue and red lines represent the low-markup and high-markup groups in the post-2000 economy, respectively. Solid lines indicate regions where firms adopt frontier technology, whereas dashed lines indicate regions without adoption. All other state variables are fixed at their long-run mean values for the respective economies. Calibration parameter values are reported in Table 3.

Figure 6: Impulse responses to a negative aggregate frontier shock (before 2000)



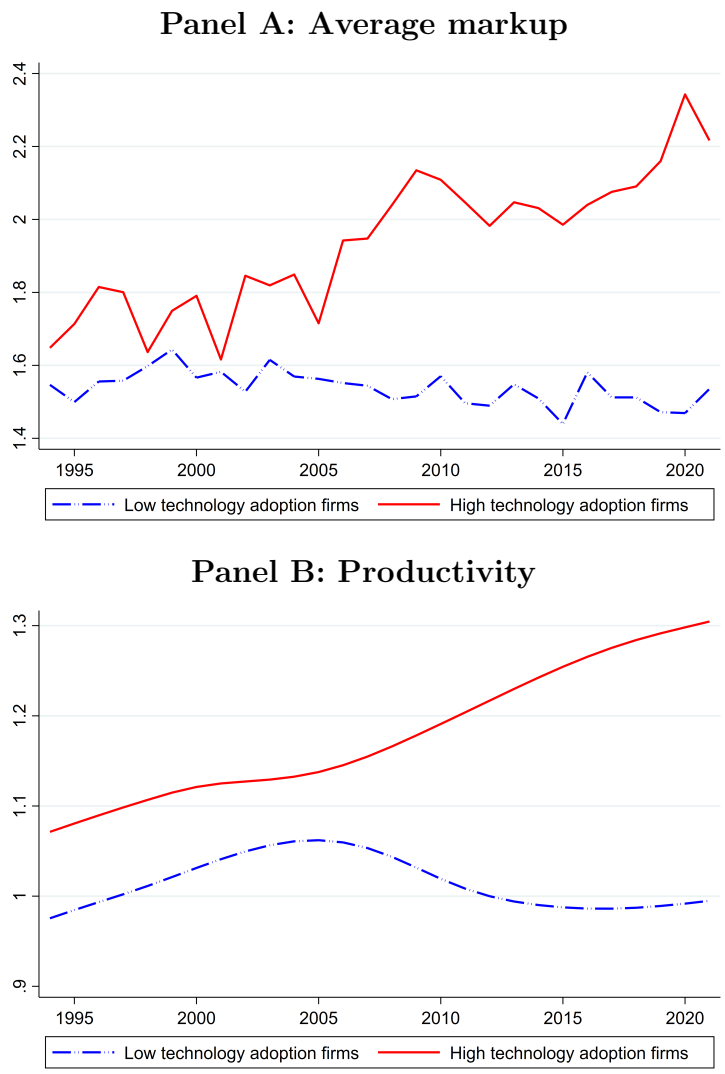
Notes: This figure presents impulse responses of selected endogenous variables in the baseline calibration of the model to a negative technology frontier shock in the quarter labeled 1. The responses are measured in percentage points deviation relative to the long-run average values for a high productivity firm (H) and a low productivity firm (L) at quarter 1. We allow normal evolution of the economy afterwards. Rev is firms' revenue, Adoption is firms' adoption choice, n is firms' technology capital, Marginal cost is firms' marginal cost $\frac{f_o}{n_t}$, Div is firms' dividends, $E_t(v_{t+1})$ is the expected firm's continuation value, BM is firms' book-to-market ratio, and SDF is the stochastic discount factor. All plots are based on 500 simulations of 200-quarter length. All variables are expressed as percentage deviations from their long-run averages.

Figure 7: Impulse responses of risk exposure and expected returns to a negative aggregate frontier shock



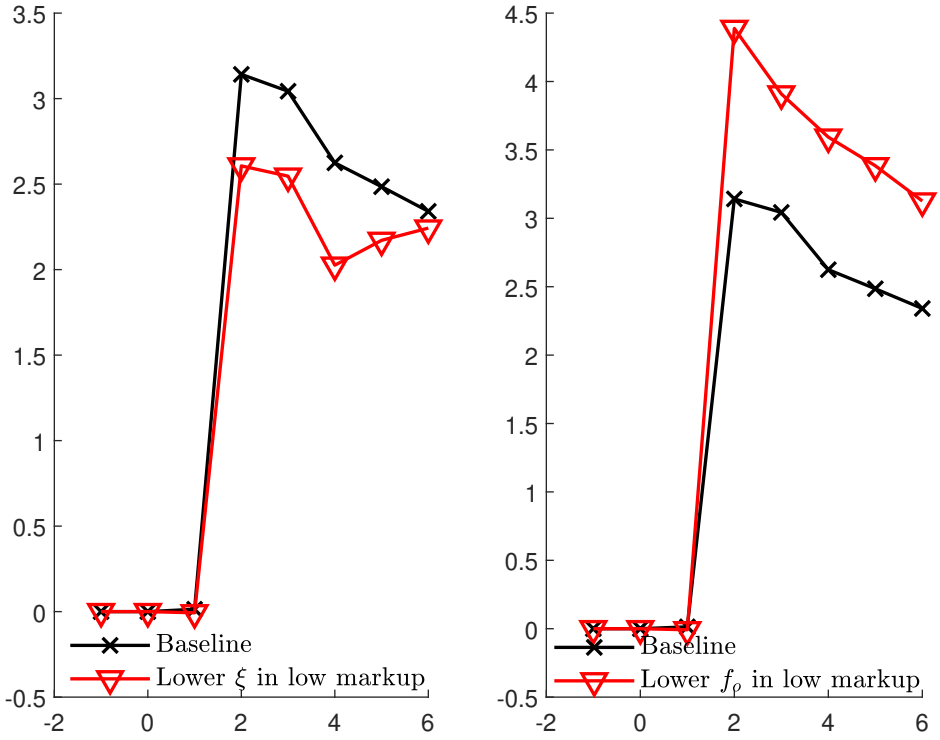
Notes: This figure presents impulse responses of the expected excess returns and risk exposure to a negative technology frontier shock in the quarter labeled 1. The responses are measured in percentage points deviation relative to the long-run average values for a high productivity firm (H) and a low productivity firm (L) at quarter 1. Columns correspond to: (i) the pre-2000 benchmark economy (left column), (ii) the post-2000 high-markup group (middle column), and (iii) the post-2000 low-markup group (right column). The expected excess return is $E_t[r^e_{j,t+1}] = \frac{E_t[v_{j,t+1}]}{p^F_{j,t}} - R^f_t$. The beta is defined from $E_t[r^e_{j,t+1}] = \lambda_t \beta_{j,t}$, and $\beta_{j,t} \equiv -\frac{\text{Cov}_t(M_{t+1}, r^e_{j,t+1})}{\text{Var}_t(M_{t+1})}$, with $\lambda_t \equiv \text{Var}_t(M_{t+1})/E_t[M_{t+1}]$. All plots are based on 500 simulations of 200-quarter length. All variables are expressed as percentage deviations from their long-run averages.

Figure 8: Markup, productivity, and technology adoption



Notes: Panel A plots the sales-weighted average markup for firms with low and high levels of technology adoption. Technology adoption is proxied by the size-adjusted frequency of technology-related keywords in annual reports. Firms are first classified into large-cap and small-cap groups based on market capitalization. Within each group, firms are sorted into terciles according to keyword frequency, with the bottom and top terciles labeled as low and high technology adoption firms, respectively. Panel B shows the trend in sales-weighted average TFP for these two groups, extracted using an HP filter with an annual smoothing parameter of 100. Due to the short history of the textual data, we do not plot the rolling-average value premium in this figure.

Figure 9: Aggregate implications for productivity



Notes: This figure presents the percentage deviations of measured aggregate TFP from their values in quarter 0 under two model specifications within the post-2000 economy calibration. The left panel compares: (i) the baseline model (black x-marks) and (ii) the model where firm demand elasticity ξ of the low-markup group is set equal to that of the high-markup group (red triangles). The right panel similarly compares the baseline model to a specification where the marginal production cost (f_o) of the low-markup group is set equal to that of the high-markup group. All plots are based on 500 simulations of 200-quarter length. We impose a positive technology frontier shock in the quarter labeled 1, allowing normal evolution of the economy afterwards.

Table 1: Increase in markups

Panel A: Aggregate markup

VARIABLES	(1) Equal weighted	(2) Asset weighted	(3) Sales weighted
Post-2000	0.26***	0.33***	0.16***
	(11.25)	(10.79)	(8.66)
Constant	1.61***	1.60***	1.50***
	(74.25)	(138.55)	(127.29)
Observations	60	60	60
Adjusted R^2	0.706	0.829	0.691

Panel B: Average markup in different groups

VARIABLES	(1) Low-markup firms	(2) High-markup firms	(3) High minus Low
Post-2000	0.00	0.54***	0.54***
	(0.05)	(11.57)	(11.52)
Constant	1.20***	2.10***	0.89***
	(415.79)	(72.52)	(32.19)
Observations	60	60	60
Adjusted R^2	-0.017	0.800	0.806

Notes: This table reports the change in the aggregate markup of all firms (Panel A) and of firms with low- and high-markups (Panel B) by regressing annual markups on the Post-2000 time dummy. A firm's individual markup is calculated annually as its sales divided by its cost of goods sold. We winsorize markups at the top and bottom 2.5%. The aggregate markup is measured as the equal-weighted, asset-weighted, and sales-weighted average markup of all firms. In Panel A, the annual aggregate markup is regressed on a dummy variable indicating whether the year is post-2000 (i.e., 2001 to 2021). In Panel B, firms are sorted into three terciles each year based on their individual markup, with cutoffs determined using the distribution of NYSE firms. We report the sales-weighted average markup of low- and high-markup firms as well as the difference in their markups. Financial firms and utilities are excluded from all calculations. The sample period spans 1962 to 2021. All t-statistics (in parentheses) are computed using Newey-West standard errors. Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Table 2: Decline in the value premium

	(1)	(2)	(3)	(4)
	Value premium	Value premium by markups		
VARIABLES	All firms	Low-markup firms	High-markup firms	High minus Low
Panel A: Pre-2000 value premium				
Constant	0.48***	0.42*	0.77***	0.35
	(2.73)	(1.91)	(3.41)	(1.53)
Observations	456	456	456	456
Panel B: Post-2000 value premium				
Constant	-0.06	0.62*	-0.30	-0.92***
	(-0.22)	(1.92)	(-0.95)	(-2.83)
Observations	246	246	246	246
Panel C: Change in value premium				
Post-2000	-0.54*	0.20	-1.07***	-1.27***
	(-1.65)	(0.51)	(-2.76)	(-3.20)
Constant	0.48***	0.42*	0.77***	0.35
	(2.73)	(1.91)	(3.41)	(1.53)
Observations	702	702	702	702
Panel D: Change in value premium, controlling for the market factor				
Post-2000	-0.86***	-0.18	-1.29***	-1.11***
	(-2.69)	(-0.48)	(-3.40)	(-2.69)
MKT	-0.15***	-0.22***	0.01	0.24***
	(-2.67)	(-3.39)	(0.20)	(4.57)
Post-2000×MKT	0.48***	0.58***	0.28***	-0.29***
	(5.03)	(5.81)	(2.61)	(-2.63)
Constant	0.55***	0.53**	0.77***	0.23
	(3.18)	(2.52)	(3.35)	(1.05)
Observations	702	702	702	702

Notes: This table reports the value premium of all firms and of low- and high-markup firms. Firms are independently sorted into terciles by markup and quintiles by book-to-market using NYSE breakpoints based on the prior year's information. Value premium is the value-weighted returns of firms in the top book-to-market quintile (value firms) minus the returns of firms in the bottom book-to-market quintile (growth firms). Low- and high-markup firms are those in the bottom and top markup tercile. Panel A shows the pre-2000 sample period (Jul 1963 to Jun 2001). Panel B presents the post-2000 sample period (Jul 2001 to Dec 2021). Panels C and D estimate the change between the two periods. T-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Table 3: Parameter values

A: Common Parameters		
Parameter	Symbol	Value
Technology: general		
Industry demand elasticity	η	4
Rate of depreciation for physical capital	δ_k	0.035
Rate of depreciation for technology capital	δ_n	0.045
Stochastic processes		
Persistence of aggregate productivity	ρ_x	0.95
Conditional volatility of aggregate productivity	σ_x	0.01
Persistence coefficient of firm-specific productivity	ρ_z	0.95
Conditional volatility of firm-specific productivity	σ_z	0.15
Persistence of aggregate technology frontier	ρ_s	0.95
Conditional volatility of aggregate technology frontier	σ_s	0.02
SDF		
Real risk-free rate	r_f	0.005
Loading of the SDF on aggregate productivity shocks	γ_x	4
Loading of the SDF on aggregate technology frontier shocks	γ_s	8.7

B: Heterogeneity in parameters				
Parameter	Symbol	Pre-2000	Post-2000	
			Low	High
Long-run mean of aggregate technology frontier	$\bar{s}$	0	0.21	0.21
Firm demand elasticity	ξ	5	8	4.1
Marginal production costs	f_o	0.19	0.25	0.04
Technology adoption costs	f_a	2.37	1.63	7
Fixed operating costs	f	5.68	4.01	255

Notes: This table presents the calibrated parameter values of the baseline model. Low and high denote the low- and high-markup groups.

Table 4: Selected moments in the data and the model: pre-2000 economy

	Data	Model
Market excess return	6.05	6.20
Market Sharpe ratio	0.39	0.39
Real risk free rate	2.06	2.00
Value premium	5.74	5.12
Value premium: CAPM alpha	6.63	2.75
Markup	1.50	1.50
Technology adoption rate	0.42	0.44
Fixed cost to sales	0.15	0.17
Net income to sales	0.05	0.05

Notes: This table reports selected moments implied by the baseline model calibration for the pre-2000 economy. We compare empirical moments ("Data") with those from simulated data ("Model"). The value premium is defined as the return difference between firms in the top and bottom book-to-market quintiles. Markup is measured as the ratio of sales to cost of goods sold. A firm is classified as adopting technology if its annual report mentions technology-related keywords more than 45 times; further details are provided in the Online Appendix. Fixed costs are proxied by SG&A expenses, excluding R&D and advertising. Net income to sales is based on net income before extraordinary items. Accounting-based variables are winsorized at the top and bottom 2.5%. Model-implied moments are the mean values across simulations. The reported statistics for the model are obtained from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations. All returns are reported as percentage per year.

Table 5: Selected data versus model-implied moments: post-2000 economy

Low markup group					High markup group				
Markup	Adoption	FC/S	NI/S	V.P.	Markup	Adoption	FC/S	NI/S	V.P.
0. Data									
1.20	0.61	0.10	0.03	7.44	2.63	0.82	0.23	0.09	-3.60
1. Baseline model									
1.34	0.62	0.11	0.03	5.34	2.66	0.82	0.20	0.09	0.15
2. More efficiency increase in frontier ($\uparrow \bar{s}$)									
1.38	0.77	0.08	0.07	0.15	2.84	0.83	0.17	0.13	0.07
3. Shutting down heterogeneity in firm demand elasticity ξ ($\downarrow \xi$ in low group)									
1.60	0.43	0.17	0.09	-0.16	2.66	0.83	0.20	0.09	0.15
4. Shutting down heterogeneity in marginal production costs f_o ($\downarrow f_o$ in low group)									
2.16	0.89	0.00	0.17	0.13	2.66	0.83	0.20	0.09	0.15
5. Shutting down heterogeneity in technology adoption costs f_a ($\downarrow f_a$ in high group)									
1.34	0.62	0.11	0.03	5.34	2.67	0.90	0.20	0.09	0.08
6. Shutting down heterogeneity in fixed operating costs f ($\downarrow f$ in high group)									
1.34	0.62	0.11	0.03	5.34	2.66	0.82	0.01	0.28	0.14
7. Zero risk price of aggregate productivity shocks ($\gamma_x = 0$)									
1.34	0.61	0.11	0.03	4.51	2.66	0.82	0.20	0.09	-0.19
8. Zero risk price of technology frontier shocks ($\gamma_s = 0$)									
1.33	0.62	0.10	0.03	0.28	2.64	0.82	0.20	0.09	0.07
9. Weaker price competition ($\uparrow$ industry demand elasticity η)									
1.36	0.90	0.01	0.14	0.18	2.67	0.83	0.18	0.11	0.01

Notes: This table presents selected moments of the data and alternative calibrations of the model for the post-2000 economy, showing the average markup (Markup), technology adoption rate (Adoption), fixed cost-to-sales ratio (FC/S), net income-to-sales ratio (NI/S), and value premium (V.P.). Specification 0 reports the data, while specification 1 presents the baseline calibration of the low-markup group and the high-markup group in the post-2000 economy. Specification 2 increases the aggregate technology frontier efficiency ($\bar{s}$) by 50% compared to the baseline calibration. Specification 3 sets firm demand elasticity (ξ) of the low markup group equal to that of the high markup group. Specification 4 sets the marginal production cost (f_o) the same as that of the high markup group. Specifications 5 and 6 adjust the technology adoption costs (f_a) and fixed operating costs (f) of the low markup group to be the same as that of the high markup group, respectively. Specification 7 sets the risk price of aggregate productivity shocks (γ_x) to zero, while specification 8 sets the risk price of aggregate technology frontier shocks (γ_s) to zero. Specification 9 increases the industry demand elasticity η for both groups.

Table 6: Technology adoption, markup, and value premium

Panel A: average markup

	(1)	(2)	(3)
Year	Low tech adoption	High tech adoption	High minus Low
1994	1.55	1.65	0.10
2021	1.54	2.22	0.68
Change in markup	-0.01	0.57	0.58

Panel B: post-2000 value premium

	(1)	(2)	(3)
VARIABLES	Low tech adoption	High tech adoption	High minus Low
Constant	0.65**	0.07	-0.57*
	(2.21)	(0.26)	(-1.72)
Observations	252	252	252
Adjusted R^2	0.000	0.000	0.000

Notes: This table presents the average markup and value premium of firms with different technology-adoption. We use size-adjusted number of keywords to quantify technology adoption. Firms are first divided into two groups based on whether their market capitalization is above the cross-sectional median. Within each size group, firms are further sorted into three terciles based on the number of technology-related keywords in their annual reports. We label firms in the top and bottom terciles of each size group as high- and low-technology-adoption firms. Panel A reports the average markup for low- and high-technology-adoption firms in 1994 and 2021 and their changes in markups. Panel B reports the value premium within low and high technology adoption firms in the period from 2001 to 2021. The value premium is calculated by independently sorting firms into quintiles based on their book-to-market ratio, then measuring the return difference between value firms (top book-to-market quintile) and growth firms (bottom book-to-market quintile) within a size-adjusted technology-adoption group. We then take the average value premium of small-cap and large-cap groups. All t-statistics (in parentheses) are computed using Newey-West standard errors. Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Table 7: Properties of the frontier shock proxy

Panel A: factor summary

	mean	median	sd	skew	kurtosis
Proxy of technology frontier shock $\tilde{s}_t$ (%)	0.0	0.1	1.5	-0.25	4.48
Annual market excess return MKT_t(%)	7.6	10.9	16.8	-0.70	2.91

Panel B: factor correlation

	$\tilde{s}_t$	MKT_t	TFP	ISO	Patent	Semiconductor	IST
Proxy of technology frontier shock $\tilde{s}_t$	100%	38%	18%	31%	27%	47%	-4%
Annual market excess return MKT_t	38%	100%	24%	-9%	12%	20%	15%

Notes: This table presents the summary statistics of asset pricing factors in Panel A and their correlation with other aggregate variables in Panel B. ΔC_t is the value-weighted average log. growth rate of COGS across all non-financial firms. ΔL_t is the value-weighted average log. growth rate of SALE across all non-financial firms. Technology frontier shock $\tilde{s}_t$ is the negative of the residuals, $-u_t$, from the following rolling regression $\Delta C_t = a + b\Delta L_t + u_t$ where the regression is run on a rolling basis with a minimum of 10 observations from 1963 to 2021. From 1963 to 1972, we set $u_t = \Delta C_t - \Delta L_t$. Other technology-related aggregate factors include the utilization-adjusted total-factor productivity (TFP), growth in the number of technology standards (ISO) (available up to 2014), growth in the number of patents (Patent), a proxy of investment-specific technology (IST) shocks based on the relative price of capital goods, and the growth of sales in the semiconductor industry (Semiconductor). More detailed definitions are in the text. The sample period is from 1963 to 2021.

Table 8: Asset pricing tests and the price of risk of technology frontier shock

Panel A: asset pricing tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1963 to 2000						2000 to 2021: low-markup firms					
	BM sorted quintile portfolios						BM sorted quintile portfolios					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
α^{CAPM}	-3.21	-2.07	-0.16	2.23	3.9	7.11	-5.6	2.89	1.42	-0.8	3.39	9.00
$[t]$	-1.73	-2.44	-0.23	1.93	2.37	2.11	-1.81	1.39	1.07	-0.47	1.89	1.90
α^{2F}	0.08	0.2	-1.32	0.53	0.38	0.3	0.18	0.65	0.07	-0.56	-0.18	-0.36
$[t]$	0.05	0.09	-1.08	0.48	0.69	0.18	0.23	0.27	0.04	-0.21	-0.15	-0.22
Cov^{MKT}	2.79	2.43	2.04	2.14	2.2	-0.59	4.1	2.1	2.65	3.04	3.33	-0.76
$[t]$	4.04	3.69	3.85	3.27	3.5	-1.24	3.1	3.5	3.07	2.46	3.02	-1.38
$Cov^{\Delta s}$	-1.21	-0.54	2.17	2.7	4.3	5.52	-4.36	7.98	7.17	4.71	12.66	17.01
$[t]$	-0.92	-0.32	1.7	1.62	2.7	2.24	-1.26	2.35	1.73	0.87	2.12	2.46

Panel B: risk factor loadings

	Pre-2000 economy (1963 to 2000)				Post-2000 economy (2000 to 2021)			
	(1)		(2)		(3)		(4)	
	CAPM	2F	CAPM	2F	CAPM	2F	CAPM	2F
b_M	3.44	0.14	3.00	1.29	2.59	-1.17	2.42	-0.20
$[t]$	2.47	0.05	2.26	0.60	1.87	-0.51	1.62	-0.08
b_S		1.28		0.78		0.68		0.55
$[t]$		2.18		2.80		2.11		1.79
MAE	2.31	0.50	1.71	1.18	2.82	0.33	2.47	1.64

Notes: This table reports the results of asset pricing tests. The two-factor (2F) model is $E[r^e_{i,t}] = \alpha_i + b_M Cov(r^e_{i,t}, MKT_t) + b_s Cov(r^e_{i,t}, \tilde{s}_t)$, in which MKT is the market factor and $\tilde{s}_t$ is the technology frontier shock proxy, and the CAPM model is the restricted case in which $b_s = 0$. Estimation is done by the GMM. Panel A reports the CAPM and the two-factor alphas of book-to-market-sorted quintile portfolios. Columns 1 to 6 focus on all firms in the pre-2000 sample period. Columns 7 to 12 focus on low-markup firms in the post-2000 sample period. The multivariate covariances between these portfolios and the factors are also reported in Panel A. Panel B reports the estimated risk loadings (b_M and b_s) using different sets of test assets. In column 1, we use five BM quintiles in the pre-2000 economy to estimate the risk loadings, which are used to compute alphas in columns 1 to 6 in panel A. In addition to the five BM quintiles, test assets in column 2 include five investment and five operating profit quintiles in the pre-2000 economy. In column 3, we use five BM quintiles among low-markup firms in the post-2000 economy to estimate risk loadings, which are used to compute alphas in columns 7 to 12 in panel A. In addition to test assets in column 3, test assets in column 4 include five investment and five operating profit quintiles in the post-2000 economy. Panel B also reports the mean absolute error (MAE) of each model. T-statistics [t] are robust to heteroskedasticity and autocorrelation (i.e., Newey-West t-stats).

Online Appendix

A Additional empirical analysis

This section describes additional robustness checks and investigates alternative explanations of our findings.

A.1 Alternative sample periods

We first examine the decline of the value premium in alternative sample periods. Table A.2 presents the results for the top-minus-bottom book-to-market quintile returns, the top-minus-bottom book-to-market decile returns, the Fama-French HML factor, and the intra-industry value premium.[30] Panel A presents the value premium after 1993, a year in which Fama and French (1993) published their influential paper on the three-factor model. Interestingly, in the post-1993 period, the value premium is no longer significant and is close to zero. The average HML factor return is less than 1% per year since 1993. Panel B reports the value premium after the financial crisis from 2011 to 2021. The average return is highly negative, although statistically insignificant. This period experiences an especially poor performance in the value premium. Anecdotal evidence suggests that the value premium suffered tremendously during the Covid-19 pandemic period. We exclude the Covid-19 period in panel C and report the value premium from 2001 to 2019. Panel C shows that even before the pandemic, the value premium has already disappeared.

A.2 Measuring markups at the industry level

In our main specification, we measure markups at the individual firm level. As a robustness check, we measure markups at the industry level. Specifically, we measure the industry sales and cost of goods sold as the total sales and cost of goods sold of all firms in the same industry. We take the ratio between the two as the industry markup and apply the same industry markup to all firms within the industry. We use 2-digit Standard Industrial Classification codes to define industries. We sort these industries into terciles each year. Table A.4 Panel A regresses the average markup of industries in the top and bottom terciles on the post-2000 dummy variables. It shows that the average markup of low-markup industries remains constant in the two periods, whereas the average markup of high-markup industries increases significantly. Table A.4 Panels B and C report the value premium of stocks in the low- and high-markup

[30] Novy-Marx (2011) and Campbell, Giglio, and Polk (2023) find that the value premium is more substantial when measured within industries. We compute the intra-industry value premium based on these papers.

industries in the pre- and post-2000 periods. Similar to our main results, in the pre-2000 period, the value premium is significant in both low- and high-markup terciles. The difference in value premium between the two groups is not significant in the pre-2000 period. On the other hand, in the post-2000 period, the value premium in the low-markup industries remains significantly positive, whereas the value premium of high-markup industries has disappeared.

A.3 Alternative markup measures

We conduct several robustness checks using alternative measures of markup to verify that the aggregate markup has increased, and most increases are concentrated among high-markup firms.

Incorporating output elasticity De Loecker, Eeckhout, and Unger (2020) use a production approach to estimate a firm's markup. The difference between their measure and ours is that their measure multiplies our measure by an output elasticity coefficient. We demonstrate that our results are robust to using their measure. Following De Loecker, Eeckhout, and Unger (2020), we measure a firm's markup as its output elasticity, θ, times its sales, $SALE$, and divided by its cost of goods sold, $COGS$. De Loecker, Eeckhout, and Unger (2020) estimate the elasticity at the industry level. In Table A.5 Panel A, we sort firms into terciles based on this alternative measure of markup. It shows that the value premium remains economically large and statistically significant in the low-markup tercile in the post-2000 period using this alternative markup definition. Table A.6 Panel A Columns 1 to 3 show that based on this measure of markup, the aggregate markup has increased significantly in the post-2000 period. Columns 4 to 6 show that the majority of the increase is from high-markup firms, consistent with our main findings.

Accounting for SG&A in markups In our main specification, we measure markup as the ratio between a company's sales and its cost of goods sold. In this section, we consider an alternative definition of the markup. In this definition, we include part of the Selling, General, and Administrative (SG&A) expenses in the cost, since the SG&A expense might not be entirely fixed. The SG&A expense item from COMPUSTAT includes some items that are outside of our model, such as R&D expenses and marketing expenses. Hence, we remove those expenses from the marginal cost.

We check whether our result that the value premium remains strong among low-markup firms is robust to measuring markups with SG&A and excluding micro-cap stocks. In Table A.5 Panel B, we sort firms into terciles based on the alternative markup definition. In this definition, we include parts of Selling, General, and Administrative (SG&A) expenses into the marginal cost. Panel B shows that the value premium remains economically large and statistically significant in the low-markup tercile in the post-2000 period using this alternative

markup definition.

Table A.6 Panel B Columns 1 to 3 show that the average markup based on this definition also increased significantly in the post-2000 period. Panel B Columns 4 to 6 show that the increase in markup is mainly driven by firms in the mid- and high-markup terciles, consistent with our main findings.

A.4 Size effect

It is well established that the value premium is lower among large-cap companies than small-cap companies. This section tests whether the rise of markups and the decline of the value premium are only observed among large-cap companies. We find that this is not the case. Even among small-cap companies, we observe that their average markup has risen and their value premium has declined. We show these findings in Figure A.1. We classify firms as large-cap or small-cap based on whether their market capitalization is above or below the NYSE median. Panel A of Figure A.1 shows that the average markup of both large- and small-cap companies has risen steadily over the past decades. The pre-2000 sales-weighted average markups of large- and small-cap companies are 1.52 and 1.40, respectively. In the post-2000 period, the average markups of large- and small-cap companies have increased to 1.69 and 1.51, respectively.

Figure A.1 Panel B shows the rolling average value premium of large- and small-cap companies. At the beginning of the sample period, the value premium in the two groups is around 0.5% per month. The value premium of small-cap companies is consistently higher than that of large-cap companies. However, we observe that both have declined. At the end of the sample, the value premium of large- and small-cap companies has declined to -0.21% and 0.18% per month, respectively. We also find that both large-cap and small-cap low-markup firms maintain a stable value premium of about 0.5% per month. In contrast, the value premium of high-markup firms, regardless of their size, has declined over time. These results are consistent with our main findings.

A.5 The rise of superstar firms

Another alternative explanation related to the size effect is the rise of superstar firms. Autor, Dorn, Katz, Patterson, and Van Reenen (2020) describe superstar firms as those with the highest productivity in an industry and capturing the most market share. They propose that the rise of superstar firms is an important explanation of the decline of the labor share in the United States. Given that the labor share and markup are theoretically related, in this section, we test whether the rise of superstar firms is the primary driver of our results. We find

that this is not the case. Following Autor, Dorn, Katz, Patterson, and Van Reenen (2020), we identify superstar firms as the largest 100 non-finance companies by sales each year. Figure A.2 Panel A shows the trend of the average markup of superstar and non-superstar firms. The two groups of firms have similar trends in their markups. Figure A.2 Panel B shows the value premium of superstar and non-superstar firms, both displaying a declining trend over time. Therefore, we do not find evidence that superstar firms are the only firms driving the rise of the aggregate markup and the decline of the value premium.

Table A.8 Panel A reports the change in the markup of superstar and non-superstar firms in the post-2000 period. We compute the average markup using different weights, such as asset-weighted, equal-weighted, and sales-weighted averages. Columns 1 to 3 show that the average markup of superstar firms increased significantly in the post-2000 period. Similarly, columns 4 to 6 show that the markup of non-superstar firms also increased significantly. Panel B reports the change of the markup of different markup terciles among superstar firms and non-superstar firms. These results are similar to our baseline findings. Most of the increase in markups is concentrated among high-markup firms, regardless of whether they are superstar or non-superstar firms.

A.6 Robustness of the cross-sectional value premium trend

We show that our findings about the cross-sectional value premium trend are not driven by micro-cap stocks or superstar stocks. In Table A.7 Panel A, we exclude micro-cap stocks when we measure the returns of BM and markup-sorted portfolios. We define micro-cap stocks as those in the bottom NYSE size decile. Panel A shows that the value premium remains significantly positive among low-markup firms in the post-2000 era, whereas the value premium of mid- and high-markup firms is not significant, consistent with our main findings. In Table A.7 Panel B, we exclude superstar firms, defined as the 100 firms with the highest sales each year. Similar to Panel A and our main findings, low-markup firms continue to have a significantly positive value premium in the post-2000 period, whereas mid- and high-markup firms no longer have significant value premium.

A.7 Trend in micro uncertainty

Herskovic, Kind, and Kung (2023) document that low-frequency cyclical movements in micro uncertainty generate value premium waves. They find that periods with elevated micro uncertainty tend to be followed by periods of elevated value premium. In this section, we verify whether the declining trend in the value premium post-2000 is driven by any declining trend in micro uncertainty. We find that this is not the case using three different measures of

micro uncertainty.

Following Herskovic, Kind, and Kung (2023) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), we measure micro uncertainty as the inter-quartile range of firm-level TFP or firm-level idiosyncratic stock returns. To measure TFP, we follow the procedures of Herskovic, Kind, and Kung (2023) or use the data from İmrohoroğlu and Tüzel (2014). We measure idiosyncratic stock return as the Fama and French (1993) three-factor alpha. Figure A.3 Panel A plots the de-trended and standardized micro uncertainty indexes. The de-trended indexes highlight the cyclical movements of micro uncertainty. We observe three noticeable peaks of micro uncertainty during the past three decades, around the 2000 dotcom bubble burst, the 2009 financial crisis, and the 2020 Covid-19 pandemic. Following these peaks, micro uncertainty declines sharply. However, these cyclical movements cannot explain the long-term decline in the value premium.

Figure A.3 Panel B plots the raw micro uncertainty index to highlight its trend. There is no noticeable decline in the long-term trend of micro uncertainty. If anything, the long-term trend of micro uncertainty appears to be increasing, which does not explain the decline in the value premium.

A.8 Alternative firm characteristics and intangible assets

We also examine whether alternative firm-level characteristics—such as profitability and intangibles—can account for the decline of the value premium. First, we find that the cross-sectional correlations between markups and various other firm characteristics are low as shown in Table A.1. For example, the correlation of markup with profitability is 12%, and with R&D expenditure is 14%. The correlations of markup with knowledge capital, organizational capital, and total intangibles are 8%, 11%, and 13%, respectively.[31] These results suggest that markups capture a distinct dimension of firm heterogeneity not spanned by intangible assets.

Next, we assess whether any of these firm characteristics can explain the decline of the value premium. To do so, we sort firms into terciles based on each characteristic and measure the value premium within these portfolios during the pre-2000 and post-2000 periods. Table A.9 shows the results. In the pre-2000 period, the value premium is significantly positive across all characteristic-sorted portfolios. However, in the post-2000 period, none of these portfolios exhibit a significant value premium. The difference in the value premium between the low- and high-characteristic portfolios is also not significant in the post-2000 period. This indicates that these firm characteristics, such as profitability and intangible assets, do not directly explain the decline in the value premium.

We also investigate the performance of the intangible-augmented value factor constructed

[31] Data on a firm's intangible capital are from the Peters and Taylor (2017) dataset.

by Eisfeldt, Kim, and Papanikolaou (2022). They add intangible assets (computed as accumulated SG&A using a perpetual-inventory method, often interpreted as organizational capital) to traditional book equity to define an intangible-adjusted book value, and show that the resulting value factor outperforms the traditional one. We find that, in our sample, the return on this intangible-augmented value factor also declines in the post-2000 period. As shown in Table A.10, its average annual return falls from 7.2% pre-2000 to 3.6% post-2000, a reduction of about 50%.[32] Thus, accounting for intangible assets strengthens the value premium, but it does not eliminate its post-2000 decline. Additionally, we find that the premium on the intangible-augmented value factor is primarily associated with the intangible-to-market component rather than the traditional book-to-market leg, suggesting that the augmented factor is naturally interpreted as capturing an organizational-capital premium that is related to, but distinct from, the classic book-to-market value premium.

A.9 The effect of new entries on the aggregate markup

We verify if the rise of the aggregate markup is driven by the entry of new firms. We find that this is not the case. Specifically, we remove firms that are less than 3 years old, 5 years old, or 10 years old from our sample and then check the aggregate change in the average markup of the remaining firms. We proxy a firm's age based on the first year it appeared in our dataset. Table A.11 reports the results. In each panel, columns 1 to 3 show the change of the equal-weighted, asset-weighted, and sales-weighted average markup of firms. They all show that the markup increased significantly in the post-2000 period. For example, even in Panel C, where we only focus on firms that are at least 10 years old, their average markup increased significantly and the magnitude of the increase is similar to Table 1. Columns 4 to 6 show that the increase in markup is mainly driven by firms in the mid-, and high-markup terciles, consistent with our main findings.

A.10 Interest rate changes and the value premium

Similar to the value premium, the interest rate has declined significantly in the past two decades. Are the two variables related, and can changes in interest rates explain changes in the value premium? We test this hypothesis and do not find supporting evidence. To do so, we regress the average value premium or changes in the value premium across different horizons (from 1 month to 10 years) on changes in interest rates over the same horizon. We consider two types of interest rates: yields on one-month treasuries and ten-year government bonds. Table A.12 reports the results. We do not find any significant relationship between the value

[32] Data are made available by Andrea L. Eisfeldt on her website.

premium and interest rates. Both panels show that changes in the interest rate are unrelated to the level or changes in the value premium over any horizon that we test. Therefore, despite the similar trends in recent years, interest rates do not reliably explain changes in the value premium. These results are consistent with the findings of Maloney and Moskowitz (2020). We also formally test whether interest rates are priced in two-factor asset pricing models (i.e., with changes in the short-term or long-term interest rate as the second factor in addition to the market factor) and find the risk loadings on the interest rate factors to be insignificant.

A.11 Construction of aggregate technology frontier proxy

For each firm j, we measure its (inflation-adjusted) COGS growth rate as the log growth of COGS:

$$\Delta c_{j,t} = \ln\left(\frac{\text{COGS}_{j,t}}{\text{COGS}_{j,t-1}}\right),$$

where COGS is deflated by the CPI. We then construct ΔC_t as the value-weighted average of $\Delta c_{j,t}$ across all nonfinancial firms, using beginning-of-period total assets as weights.

Similarly, for each firm j, we measure its (inflation-adjusted) revenue growth rate as the log growth of sales:

$$\Delta l_{j,t} = \ln\left(\frac{\text{Sale}_{j,t}}{\text{Sale}_{j,t-1}}\right),$$

where sales are also deflated by the CPI. We then construct ΔL_t as the value-weighted average of $\Delta l_{j,t}$ across all nonfinancial firms, again using beginning-of-period total assets as weights.

Using the annual series $\{\Delta C_t, \Delta L_t\}$ from 1963 to 2021, we estimate the following regression on a rolling basis:

$$\Delta C_t = a + b\Delta L_t + u_t. \tag{24}$$

We require at least 10 years of data to run each rolling regression, so the first regression-based residual u_t is obtained for 1972. For the earlier years 1963–1971, we simply set

$$u_t = \Delta C_t - \Delta L_t.$$

In the full sample, the estimated coefficient on ΔL_t is close to one and the estimated constant term a is close to zero, suggesting that aggregate revenue and operating costs are approximately cointegrated. Consistent with the main text, we use the negative of the residuals as our proxy for the technology frontier shock, i.e.,

$$\text{Technology frontier shock at time } t \equiv -u_t.$$

Intuitively, a positive technology frontier shock corresponds to unexpectedly low aggregate

growth in variable production costs, conditional on aggregate revenue growth.

B Estimation of technology adoption rates

This section provides more detailed descriptions of how we compute and calibrate companies' rate of technology adoption. To measure the likelihood of a company to adopt new technologies, we apply textual analysis to the company's annual reports. We obtained the cleaned text data of 10-K filings of publicly traded US firms from Loughran-McDonald website.[33] The data starts from 1994, which marks the beginning of our textual analysis. We link the text data with COMPUSTAT using the CIK-GVKEY link table from SEC Analytics Suite by WRDS.

We identify technology-related content in each company's 10-K filing by counting occurrences of root keywords—technology, system, software, and data—as well as their derivatives, such as technologies and technological. Our results are robust to the inclusion of these variations. This exercise yields an annual keyword count for each firm in our sample from 1994 to 2021. We classify a firm as having adopted new technology in a given year if its 10-K mentions technology-related keywords more than 45 times. The threshold of 45 is chosen so that the average technology adoption rate in the post-2000 period is 73%, consistent with the European Investment Bank Investment Survey (2022), which reports that 73% of U.S. firms adopted advanced digital technologies such as advanced robotics, 3D printing, big data analytics, and artificial intelligence.

Using this threshold, we compute the technology adoption rate in the pre-2000 period to be 42%, meaning that 42% of firms mentioned technology-related keywords more than 45 times in their 10-K filings. We also compute the technology adoption rate of low- and high-markup companies in the post-2000 period. On average, 61% of firms in the low-markup tercile adopt new technologies, compared to 82% in the high-markup tercile.

C Proof of Propositions

C.1 Proof of Proposition 1

Proof. First of all, we define the intraperiod profit maximization problem. As we fix period t and the state $\Theta_t = (k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t)$, installed capital $k_{j,t}$ and productivities $(X_t, z_{j,t})$

[33] Link to the website is at: https://sraf.nd.edu/sec-edgar-data/

determine predetermined capacity

$$y_{j,t} = X_t z_{j,t} k_{j,t} > 0. \tag{25}$$

Given technology capital $n_{j,t}$, variable cost is

$$oc_{j,t} = \rho(n_{j,t})\, y_{j,t}, \qquad \rho(n_{j,t}) = \frac{f_o}{n_{j,t}}. \tag{26}$$

For the intraperiod pricing decision we can ignore terms that do not depend on $p_{j,t}$, such as adoption costs and fixed operating costs. Hence, conditional on $n_{j,t}$, firm j sets $p_{j,t} > 0$ to maximize the profit function

$$\pi_{j,t}(p_{j,t}) = p_{j,t} y_{j,t} - \rho(n_{j,t})\, y_{j,t}, \tag{27}$$

subject to

$$d\left(p_{j,t}; Q_t, P_t\right) \;\geq\; y_{j,t}, \qquad \text{i.e.} \qquad Q_t \left(\frac{p_{j,t}}{P_t}\right)^{-\xi} \;\geq\; y_{j,t}. \tag{28}$$

Since $y_{j,t} > 0$ is fixed, $\pi_{j,t}(p_{j,t})$ is an affine (strictly increasing) function of $p_{j,t}$ with slope $y_{j,t}$.

Then we turn to several properties of the demand function. With the assumption that $Q_t > 0$, $P_t > 0$, and $\xi > 0$, the derivative of the demand function is

$$d'\left(p_{j,t}; Q_t, P_t\right) = \frac{\partial}{\partial p_{j,t}} \left[Q_t \left(\frac{p_{j,t}}{P_t}\right)^{-\xi} \right] \tag{29}$$

$$= Q_t \cdot (-\xi) \left(\frac{p_{j,t}}{P_t}\right)^{-(\xi+1)} \cdot \frac{1}{P_t} \tag{30}$$

$$= -\,\xi\, Q_t \left(\frac{p_{j,t}}{P_t}\right)^{-(\xi+1)} \frac{1}{P_t} < 0 \qquad \text{for all } p_{j,t} > 0, \tag{31}$$

so d_t is strictly decreasing and continuous on $(0, \infty)$. Moreover,

$$\lim_{p_{j,t} \downarrow 0} d\left(p_{j,t}; Q_t, P_t\right) = \lim_{p_{j,t} \downarrow 0} Q_t \left(\frac{p_{j,t}}{P_t}\right)^{-\xi} = +\infty, \tag{32}$$

$$\lim_{p_{j,t} \uparrow \infty} d\left(p_{j,t}; Q_t, P_t\right) = \lim_{p_{j,t} \uparrow \infty} Q_t \left(\frac{p_{j,t}}{P_t}\right)^{-\xi} = 0. \tag{33}$$

which implies there exists a unique $p_{j,t} > 0$ such that $d\left(p_{j,t}; Q_t, P_t\right) = y_{j,t}$ for any given $y_{j,t} > 0$

.

Consequently, the constrained maximization problem (27)–(28) can be written as

$$\max_{p_{j,t}>0} \pi_{j,t}(p_{j,t}) \quad \text{subject to} \quad d\left(p_{j,t}; Q_t, P_t\right) - y_{j,t} \geq 0.$$

Form the Lagrangian

$$\mathcal{L}(p_{j,t}, \lambda_{j,t}) = p_{j,t} y_{j,t} - \rho(n_{j,t}) y_{j,t} + \lambda_{j,t}\big(d\left(p_{j,t}; Q_t, P_t\right) - y_{j,t}\big), \qquad \lambda_{j,t} \geq 0. \tag{34}$$

The Karush–Kuhn–Tucker (KKT) first-order conditions are:

$$\frac{\partial \mathcal{L}}{\partial p_{j,t}} = y_{j,t} + \lambda_{j,t} d'\left(p_{j,t}; Q_t, P_t\right) = 0, \tag{35}$$

$$\lambda_{j,t} \geq 0, \quad d\left(p_{j,t}; Q_t, P_t\right) - y_{j,t} \geq 0, \quad \lambda_{j,t}\big(d\left(p_{j,t}; Q_t, P_t\right) - y_{j,t}\big) = 0. \tag{36}$$

Now we prove the demand–capacity constraint binds and the uniqueness of the optimal price. Suppose, for contradiction, that at an optimum $(p^\star_{j,t}, \lambda^\star_{j,t})$, the constraint is slack:

$$d\left(p^\star_{j,t}; Q_t, P_t\right) > y_{j,t}.$$

Then by complementary slackness (36) we must have $\lambda^\star_{j,t} = 0$, and the stationarity condition (35) becomes

$$y_{j,t} = 0.$$

This contradicts $y_{j,t} > 0$. Therefore at the optimum the constraint must bind:

$$d\left(p^\star_{j,t}; Q_t, P_t\right) = y_{j,t}. \tag{37}$$

Since $d(\cdot)$ is strictly decreasing and continuous by (31), (33), there is a unique $p^\star_{j,t} > 0$ satisfying (37).

Substituting the definition of the demand function into (37) yields

$$Q_t \left(\frac{p^\star_{j,t}}{P_t}\right)^{-\xi} = y_{j,t} = X_t z_{j,t} k_{j,t}. \tag{38}$$

Divide both sides by $Q_t > 0$:

$$\left(\frac{p^\star_{j,t}}{P_t}\right)^{-\xi} = \frac{X_t z_{j,t} k_{j,t}}{Q_t}. \tag{39}$$

Raise both sides to the power $-1/\xi$ (well-defined since $\xi > 0$):

$$\frac{p^{\star}_{j,t}}{P_t} = \left(\frac{X_t z_{j,t} k_{j,t}}{Q_t}\right)^{-1/\xi}. \tag{40}$$

Multiply both sides by $P_t > 0$:

$$p^{\star}_{j,t} = P_t \left(\frac{X_t z_{j,t} k_{j,t}}{Q_t}\right)^{-1/\xi}. \tag{41}$$

Using $Q_t = P_t^{-\eta}$, we rewrite the fraction

$$\frac{X_t z_{j,t} k_{j,t}}{Q_t} = X_t z_{j,t} k_{j,t} \cdot P_t^{\eta},$$

so (41) becomes

$$\begin{aligned} p^{\star}_{j,t} &= P_t \left(X_t z_{j,t} k_{j,t} \cdot P_t^{\eta}\right)^{-1/\xi} && (42)\\ &= P_t \left(X_t z_{j,t} k_{j,t}\right)^{-1/\xi} \cdot P_t^{-\eta/\xi} && (43)\\ &= P_t^{1-\eta/\xi} \left(X_t z_{j,t} k_{j,t}\right)^{-1/\xi}. && (44) \end{aligned}$$

This is exactly the formula in (18).

Finally, we can figure out the marginal cost and markup. From (26), variable operating cost is linear in $y_{j,t}$, so

$$MC_{j,t} = \frac{\partial oc_{j,t}}{\partial y_{j,t}} = \rho(n_{j,t}) = \frac{f_o}{n_{j,t}}. \tag{45}$$

If $\phi_{j,t} = 1$ (adoption), $n_{j,t} = S_t$ (by the law of motion for technology capital), and

$$MC_{j,t} = \frac{f_o}{S_t}. \tag{46}$$

If $\phi_{j,t} = 0$ (no adoption), $n_{j,t} = (1 - \delta_n) n_{j,t-1}$, so

$$MC_{j,t} = \frac{f_o}{(1 - \delta_n) n_{j,t-1}}. \tag{47}$$

The markup is defined as

$$\mu_{j,t} = \frac{p^{\star}_{j,t}}{MC_{j,t}}. \tag{48}$$

Combining (44) and (46), we obtain the markup in the adoption case

$$\mu_{j,t} = p^{\star}_{j,t} \cdot \frac{S_t}{f_o} \tag{49}$$

$$= P_t^{1-\eta/\xi}\left(X_t z_{j,t} k_{j,t}\right)^{-1/\xi} \cdot \frac{S_t}{f_o}. \tag{50}$$

Combining (44) and (47), we obtain the markup in the no-adoption case

$$\mu_{j,t} = p^{\star}_{j,t} \cdot \frac{(1-\delta_n) n_{j,t-1}}{f_o} \tag{51}$$

$$= P_t^{1-\eta/\xi}\left(X_t z_{j,t} k_{j,t}\right)^{-1/\xi} \cdot \frac{(1-\delta_n) n_{j,t-1}}{f_o}. \tag{52}$$

Equations (50) and (52) coincide with the two cases in (19). □

C.2 Proof of Proposition 2

Proof. The Bellman equation for firm j at period t can be written as

$$v_{j,t}(\Theta_t) = \max_{\phi_{j,t}\in\{0,1\},\, i_{j,t}} \left\{ \mathrm{div}_{j,t}(\phi_{j,t}, i_{j,t}) + \mathbb{E}_t\left[M_{t,t+1} v_{j,t+1}(\Theta_{t+1})\right] \right\} \tag{53}$$

$$= \max\left\{ div^{\text{adopt}}_{j,t} + \mathbb{E}_t\left[M_{t,t+1} v^{\text{adopt}}_{j,t+1}\right],\ div^{\text{noadopt}}_{j,t} + \mathbb{E}_t\left[M_{t,t+1} v^{\text{noadopt}}_{j,t+1}\right] \right\}. \tag{54}$$

.

Hence firm j adopts the frontier technology at date t (i.e., chooses $\phi_{j,t} = 1$) if and only if the value of adopting is at least as large as the value of not adopting:

$$div^{\text{adopt}}_{j,t} + \mathbb{E}_t\left[M_{t,t+1} v^{\text{adopt}}_{j,t+1}\right] \ \geq\ div^{\text{noadopt}}_{j,t} + \mathbb{E}_t\left[M_{t,t+1} v^{\text{noadopt}}_{j,t+1}\right].$$

Rearranging terms yields equation (20).

□

D Numerical Algorithm

This section describes the solution algorithm for the model, which follows the generalized approach in solving heterogeneous agents models (e.g., Krusell and Smith (1998)).

Using Proposition 1, we first solve the firm's static pricing problem conditional on capacity $y_{j,t} = X_t z_{j,t} k_{j,t}$ and show that the demand–capacity constraint $d(p_{j,t}; Q_t, P_t) \geq y_{j,t}$ always binds. This yields a closed-form optimal price $p^{\star}_{j,t}$ and implied revenue and marginal costs as

functions of the state. In the numerical solution below, we therefore treat prices as already set at $p^{\star}_{j,t}$ and solve the dynamic problem only over investment $i_{j,t}$ and adoption $\phi_{j,t}$.

D.1 Solving the monopolistic competitive equilibrium

The Bellman equation for the firm problem is as follows:

$$v\left(k, n_{-1}, z; X, S, \chi\right) = \max_{\{i,\phi\}} \left\{ \begin{array}{c} (rev - oc - i - h - ac - f) \\ +E\left[M' v\left(k', n, z', ; X', S', \chi'\right)\right] \end{array} \right\}.$$

The aggregate state of the economy is (X, S, χ). Then the evolution of the aggregate economy can be characterized by the mappings below:

$$\begin{aligned} P &= \Gamma_P\left(X, S, \chi\right) \\ \chi' &= \Gamma_\chi\left(X, S, \chi\right). \end{aligned}$$

Note that the industry state, namely the cross-sectional distribution χ is generally intractable as a state variable, so we approximate the cross-sectional distribution χ in the aggregate state space by the aggregate capital $K = \int k\left(k, n_{-1}, z\right) d\chi$, which implies that the approximate aggregate state vector is given by $\left(X, S, K\right)$. We then define the approximation to the equilibrium mapping Γ_P and Γ_χ using the log-linear rules as below:

$$\begin{aligned} \hat{\Gamma}_P &: \log(\hat{P}) = \alpha_P\left(X, S\right) + \beta_P\left(X, S\right)\log(K) \\ \hat{\Gamma}_K &: \log(\hat{K}') = \alpha_K\left(X, S\right) + \beta_K\left(X, S\right)\log(K). \end{aligned}$$

We test the internal accuracy of the approximation using statistics commonly used in the literature on heterogeneous agents models with aggregate uncertainty. Now the approximated Bellman equation is given by

$$v\left(k, n_{-1}, z, ; X, S, K\right) = \max_{\{i,\phi\}} \left\{ \begin{array}{c} (rev - oc - i - h - ac - f) \\ +E\left[M' v\left(k', n, z'; X', S', K'\right)\right] \end{array} \right\}.$$

Now we describe our solution algorithm details. We first initialize the forecast rules $\hat{\Gamma}^{(1)}_P$ and $\hat{\Gamma}^{(1)}_K$ with guessed initial coefficients $\alpha^{(1)}_P\left(X, S\right)$ and $\beta^{(1)}_P\left(X, S\right)$, and $\alpha^{(1)}_K\left(X, S\right)$ and $\beta^{(1)}_K\left(X, S\right)$. Then the following steps are performed with iteration $q = 1, 2, ...$to implement the algorithm:

Step 1: Solve the firm problem as in the Bellman equation for v given the forecast rules $\hat{\Gamma}^{(q)}_P$ and $\hat{\Gamma}^{(q)}_K$. This gives approximated firm value function $v^{(q)}$ and policy functions $\left(\hat{\imath}^{(q)}, \hat{\phi}^{(q)}\right)$.

Step 2: Simulate the economy for T periods unconditionally. During this simulation, we

do not impose adherence of the assumed equilibrium pricing mapping $\hat{\Gamma}_P$.

Step 3: Update the forecast rules of $\hat{\Gamma}_P^{(q)}$ and $\hat{\Gamma}_K^{(q)}$ to get $\hat{\Gamma}_P^{(q+1)}$ and $\hat{\Gamma}_K^{(q+1)}$ using the simulated data from step 2.

Step 4: Check the convergence. Keep doing the iteration until the difference between $(\hat{\Gamma}_P^{(q)}, \hat{\Gamma}_K^{(q)})$ and $(\hat{\Gamma}_P^{(q+1)}, \hat{\Gamma}_K^{(q+1)})$ is smaller than a predetermined criterion ϵ_Γ, then stop and exit the algorithm.

In the following, we discuss how we implement each step in detail numerically.

Firm Problem We use the value function iteration procedure to solve the firm's maximization problem numerically. We specify the grids of 300 points for capital with upper bounds $\bar{k}$ and $\bar{n}_{-1}$ that are large enough to be nonbinding. The grid for capital is constructed recursively given the pre-specified lower and upper bounds $\underline{k}$ and $\bar{k}$, following $k_i = k_{i-1}/(1-\delta)$, where $i = 1, \ldots, s$ is the index of grid points. The grid for technology capital is constructed log-linearly. We discretize the aggregate and firm-specific productivities with 5 (productivity level) states process using Rouwenhorst (1995), respectively. In all cases, the results are robust to finer grids for the level of productivity process as well. Once the discrete state space is available, the conditional expectation can be carried out simply as a matrix multiplication. Finally, we use a simple discrete global search routine in maximizing the firm's problem.

To set the grid of the technology capital $\hat{n}_t = \log(n_t)$, we let $\hat{n}_{nN} = \bar{s}(\mathcal{T}) + 3\sigma_s$. To make sure the technology capital is on the grids, for any $m \in [1, nN-1]$, we set $\hat{n}_m = \hat{n}_{nN} + (nN-m)\log(1-\delta_n)$ where we choose the number of grids nN such that $\hat{n}_1 < \bar{s}(\mathcal{T}) - 3\sigma_s$. After that, for any $j \in [1, n_s]$, we let $s_j = \hat{n}_{m'(j)}$ where $m'(1) = 1$, $m'(n_s) = nN$, and $m'(j+1) - m'(j)$ almost has the same distance. In the end, given the grids of s, we calculate the transition matrix $rev^S_{j \to j'}$.

Unconditional Simulation and Market Clearing We simulate the model for $T = 5000$ periods of aggregate productivity, uncertainty and financial cost realizations $(X_t, S_t), t = 1, \ldots, T$ following the exogenous processes which remain the same for steps 1-4. To compute the aggregate variables, we follow the histogram-based approach by Young (2010), which avoids the Monte Carlo sampling error in the simulation of individual firms. Specifically, we compute the distribution (histogram) on the firm-specific state points (k, n_{-1}, z) in each period, i.e., $\chi_{t+1}\left((k', n, z')_j\right) = \sum \chi_t\left((k, n_{-1}, z)_i\right) \prod\left(z_i, z'_j\right) 1\left(k'_j = k'_t\left((k, n_{-1}, z)_i\right), n_j = n_t\left((k, n_{-1}, z)_i\right)\right)$, where $(k, n_{-1}, z)_i$ are discretized individual states for $\mathrm{i} = 1, \ldots, \mathrm{n_k n_n n_z}$ and $\prod\left(z_i, z'_j\right)$ is the transition matrix for firm-specific productivity.

In each simulation period t, we make the individual firm policy functions to be consistent with market clearing and the firm optimization, that is the simulated aggregate price P_t and the market clearing industry price $p = Y^{-\frac{1}{\eta}}$ are consistent with the approximate cross-sectional distribution and the firm individual policy rules.

Equilibrium Mapping Update To update the equilibrium mappings $\hat{\Gamma}_p^{(q)}$ and $\hat{\Gamma}_K^{(q)}$, we first discard the 500 initial periods in simulation, then we run the following regressions on the simulated data to $\hat{\Gamma}_P^{(q)}$ and $\hat{\Gamma}_K^{(q)}$,

$$\begin{aligned}\log(p_t) &= \alpha_p(X_t, S_t) + \beta_p(X_t, S_t)\log(K_t)\\ \log(K_{t+1}) &= \alpha_K(X_t, S_t) + \beta_K(X_t, S_t)\log(K_t).\end{aligned}$$

After collecting the estimated coefficients, we get updated forecasted rules $\hat{\Gamma}_p^{(q+1)}$ and $\hat{\Gamma}_K^{(q+1)}$.

Test for Convergence To determine convergence, one can check if the maximum absolute difference between two forecasting rules is smaller than a predetermined tolerance. In the following, we use a commonly accepted practice to check the internal accuracy of a forecast mapping based on the maximum Den Haan (2010) statistics. Let $\mathrm{DH}_k^{\max}$ and $\mathrm{DH}_p^{\max}$ denote the Den Haan statistics for aggregate capital K and price p, respectively, which are maximum absolute log difference between actual simulated (K_t, p_t) and the forecasted (K_t, p_t) using the equilibrium mappings $\hat{\Gamma}_p$ and $\hat{\Gamma}_K$. The forecast mapping converge when

$$\max\left\{\left|DH_k^{\max,q+1} - DH_k^{\max,1}\right|, \left|DH_p^{\max,q+1} - DH_p^{\max,1}\right|\right\} < \epsilon,$$

where $\epsilon = 1\%$.

Internal accuracy of the approximation This section reports the basic accuracy statistics to evaluate the accuracy of heterogeneous-agents models with aggregate uncertainty used in the literature. We show that the R^2 implied by the following forecasting regressions for price $\hat{p}_t$ and aggregate capital $\hat{K}_{t+1}$ are close to 1:

$$\begin{aligned}\log(p_t) &= \alpha_p(X_t, S_t) + \beta_p(X_t, S_t)\log(K_t)\\ \log(K_{t+1}) &= \alpha_K(X_t, S_t) + \beta_K(X_t, S_t)\log(K_t).\end{aligned}$$

D.2 Solving the Bellman equation

We apply the value function iteration to solve the following economy:

$$v_t\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right) = \max_{i_t,\, \phi_t} \left\{ div_t + E_t\left[M_{t+1} v_{t+1}\left(k_{t+1}, n_t, z_{t+1}, X_{t+1}, S_{t+1}, K_{t+1}\right)\right]\right\}$$

$$s.t.\ div_t = rev_t - i_t - h_t - oc_t - ac_t - f, \tag{55}$$

$$\text{where } oc_t = \begin{cases} \frac{f_o}{S_t} y_t & \text{if } \phi_t = 1 \\ \frac{f_o}{(1-\delta_n) n_{t-1}} y_t & \text{if } \phi_t = 0 \end{cases}, \tag{56}$$

$$ac_t = \begin{cases} f_a & \text{if } \phi_t = 1 \\ 0 & \text{if } \phi_t = 0 \end{cases}, \tag{57}$$

$$n_t = \begin{cases} S_t, & \text{if } \phi_t = 1 \\ (1-\delta_n) n_{t-1}, & \text{if } \phi_t = 0 \end{cases}, \tag{58}$$

$$h_t = \begin{cases} \left(S_t - (1-\delta_n) n_{t-1}\right) \cdot 1_{\{S_t - (1-\delta_n) n_{t-1} > 0\}}, & \text{if } \phi_t = 1 \\ 0, & \text{if } \phi_t = 0 \end{cases}. \tag{59}$$

$$k_{t+1} = (1-\delta_k)\, k_t + i_t$$

$$x_{t+1} = \rho_x x_t + \sigma_x \varepsilon^x_{t+1}$$

$$z_{t+1} = \rho_z z_t + \sigma_z \varepsilon^z_{t+1}$$

$$s_{t+1} = (1-\rho_s)\, \bar{s}\left(\mathcal{T}\right) + \rho_s s_t + \sigma_s \varepsilon^s_{t+1},$$

where $x_t = \log\left(X_t\right)$, $z_t = \log\left(Z_t\right)$, and $s_t = \log\left(S_t\right)$.

To solve the above economy, we need to solve the following two economies separately:

(1) When $\phi_t = 0$, i.e., there is no adoption:

$$\tilde{v}^1_t\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right) = \max_{i_t} \left\{ div_t + E_t\left[M_{t+1} v_{t+1}\left(k_{t+1}, n_t, z_{t+1}, X_{t+1}, S_{t+1}, K_{t+1}\right)\right]\right\}$$

$$s.t.\ div_t = rev_t - i_t - h_t - oc_t - ac_t - f, \tag{60}$$

$$\text{where } oc_t = \frac{f_o}{(1-\delta_n)\, n_{t-1}} y_t, \tag{61}$$

$$ac_t = 0, \tag{62}$$

$$n_t = (1-\delta_n) n_{t-1}, \tag{63}$$

$$k_{t+1} = (1-\delta_k)\, k_t + i_t$$

$$x_{t+1} = \rho_x x_t + \sigma_x \varepsilon^x_{t+1}$$

$$z_{t+1} = \rho_z z_t + \sigma_z \varepsilon^z_{t+1}$$

$$s_{t+1} = (1-\rho_s)\, \bar{s}\left(\mathcal{T}\right) + \rho_s s_t + \sigma_s \varepsilon^s_{t+1},$$

Under the case $\phi_t = 0$, their technology capital depreciates at the rate of δ_n. This implies, if at time $t+1$, the grid of n_t is at n_{m-1}, then the grid of n_{t-1} is at n_m from equation (63). Therefore, numerically we solve the Bellman equation through

$$\tilde{v}_t^1\left(k_i, n_m, z_p, X_q, S_j, K_l\right) = \max_{i_t}\left\{div_t + \sum_{q'=1}^{n_x}\sum_{j'=1}^{n_s}\sum_{p'=1}^{n_z}\pi_{q\to q'}^X\pi_{j\to j'}^S\pi_{p\to p'}^z v_{t+1}\left(k_{i'}, n_{m-1}, z_{p'}, X_{q'}, S_{j'}, K_{l'}\right)\right\}$$

(2) When $\phi_t = 1$, i.e., there is adoption:

$$\tilde{v}_t^2\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right) = \max_{i_t}\left\{div_t + E_t\left[M_{t+1}v_{t+1}\left(k_{t+1}, n_t, z_{t+1}, X_{t+1}, S_{t+1}, K_{t+1}\right)\right]\right\}$$

$$s.t.\ div_t = rev_t - i_t - h_t - oc_t - ac_t - f, \tag{64}$$

$$\text{where } oc_t = \frac{f_o}{S_t}y_t, \tag{65}$$

$$ac_t = f_a, \tag{66}$$

$$n_t = S_t, \tag{67}$$

$$h_t = \left(S_t - (1-\delta_n)n_{t-1}\right)\cdot 1_{\{S_t-(1-\delta_n)n_{t-1}>0\}}. \tag{68}$$

$$k_{t+1} = (1-\delta_k)\,k_t + i_t$$

$$x_{t+1} = \rho_x x_t + \sigma_x\varepsilon_{t+1}^x$$

$$z_{t+1} = \rho_z z_t + \sigma_z\varepsilon_{t+1}^z$$

$$s_{t+1} = (1-\rho_s)\,\bar{s}\left(\mathcal{T}\right) + \rho_s s_t + \sigma_s\varepsilon_{t+1}^s,$$

Under the case $\phi_t = 1$, we know the firms choose to adopt and the technology capital jumps to the technology frontier, i.e., $n_t = S_t$. This implies that numerically we solve the Bellman equation through

$$\tilde{v}_t^2\left(k_i, n_m, z_p, X_q, S_j, K_l\right) = \max_{i_t}\left\{div_t + \sum_{q'=1}^{n_x}\sum_{j'=1}^{n_s}\sum_{p'=1}^{n_z}\pi_{q\to q'}^X\pi_{j\to j'}^S\pi_{p\to p'}^z v_{t+1}\left(k_{i'}, n_{m'(j)}, z_{p'}, X_{q'}, S_{j'}, K_{l'}\right)\right\}$$

where $n_{m'(j)} = S_j$.

After we solve these two cases, we let

$$v_t\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right) = \max\left\{\tilde{v}_t^1\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right),\ \tilde{v}_t^2\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right)\right\}$$

which will tell us whether $\phi_t\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right)$ is 0 or 1.

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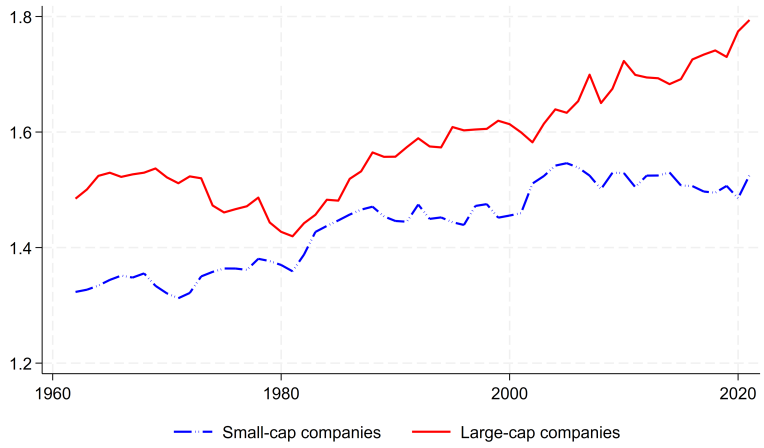
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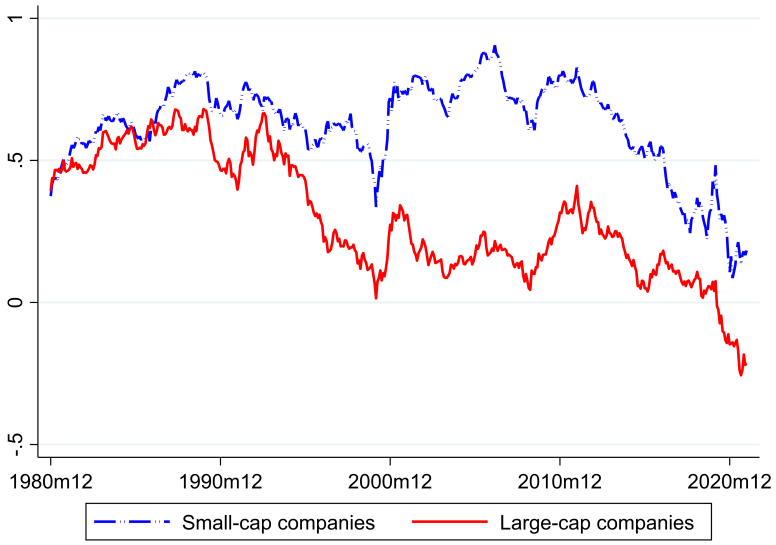
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Figure A.1: Markup and value premium of large- and small-cap companies

Panel A: average markup of large- and small-cap companies



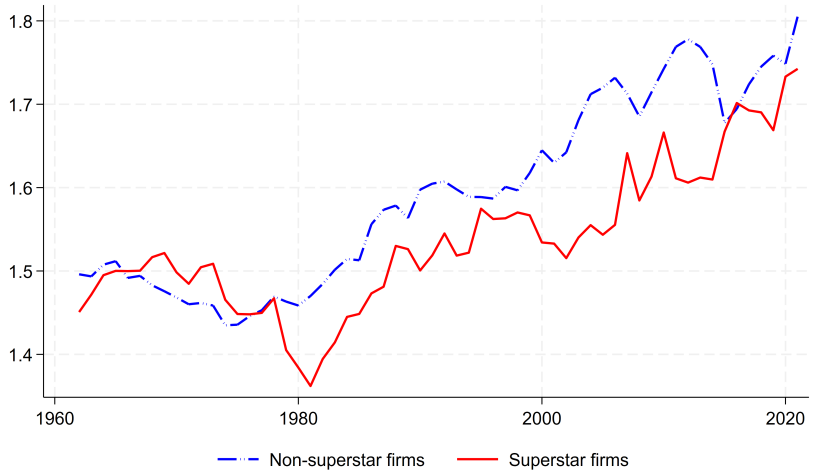
Panel B: value premium among large- and small-cap companies



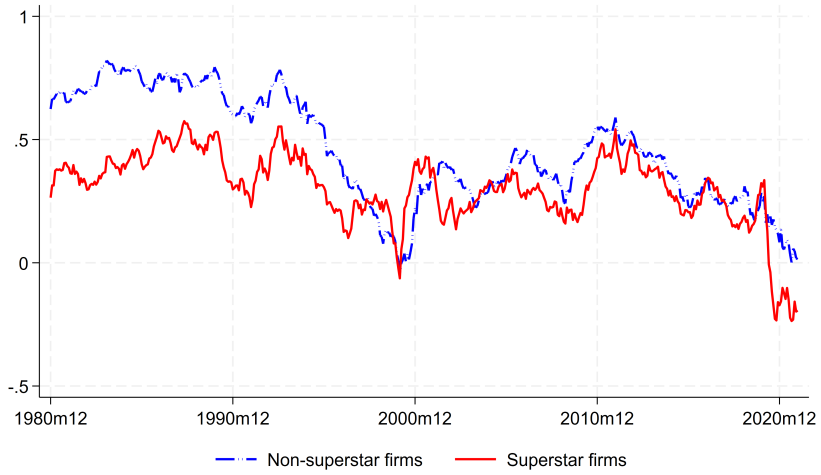
Notes: Panel A of this figure plots the sales-weighted average markup of large-cap and small-cap companies. We define large-cap and small-cap companies as those with market capitalizations above and below the NYSE median. Panel B plots the 20-year (backward) rolling average value premium (in percentage per month) among large-cap and small-cap companies. We measure the value premium as the difference in return between firms in the top book-to-market quintile (value firms) and firms in the bottom book-to-market quintile (growth firms).

Figure A.2: Markup and value premium of superstar and non-superstar firms

Panel A: average markup of superstar and non-superstar firms



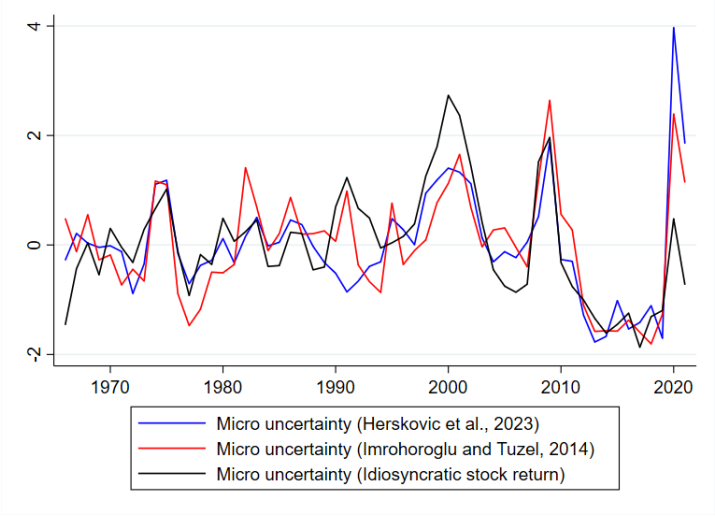
Panel B: value premium among superstar and non-superstar firms



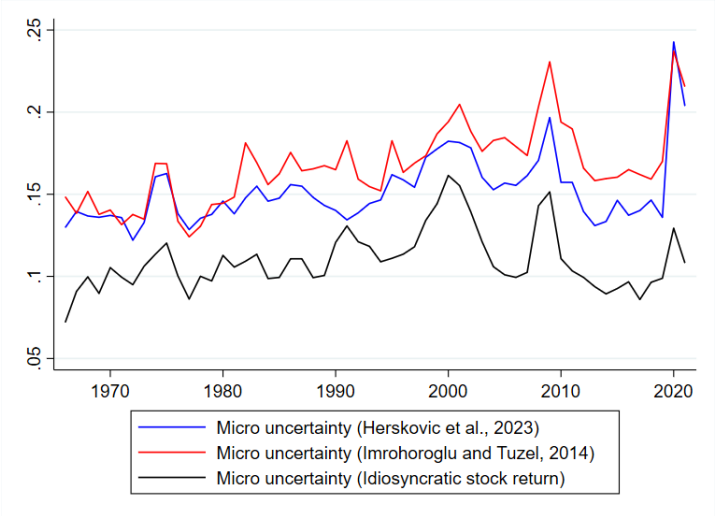
Notes: Panel A plots the sales-weighted average markup of superstar and non-superstar firms. We define superstar firms as the top 100 publicly traded non-finance firms in the US in terms of total sales each year. Panel B plots the 20-year (backward) rolling average value premium (in percentage per month) among superstar and non-superstar firms. We measure the value premium as the difference in return between firms in the top book-to-market quintile (value firms) and firms in the bottom book-to-market quintile (growth stocks).

Figure A.3: Micro uncertainty indexes: de-trended and raw index

Panel A: micro uncertainty (de-trended and standardized)



Panel B: micro uncertainty (raw)



Notes: This figure plots the micro uncertainty indexes from 1965 to 2021. Panel A plots the de-trended and standardized micro uncertainty indexes. Panel B plots the raw micro uncertainty indexes. Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), we measure micro uncertainty as the inter-quartile range of idiosyncratic firm-level TFP or firm-level idiosyncratic return. We measure TFP following the procedure of Herskovic, Kind, and Kung (2023) (the blue line) or İmrohoroğlu and Tüzel (2014) (the red line). We measure idiosyncratic stock return as the Fama and French (1993) three-factor alpha (the black line).

Table A.1: Cross-sectional correlation between markup and stock characteristics

Panel A: full sample

	Markup	Size	BM	ROA	R&D	Int. K	Know. K	Org. K
Markup	1.00							
Size	0.09	1.00						
BM	-0.14	-0.35	1.00					
ROA	0.12	0.34	-0.05	1.00				
R&D	0.13	-0.10	-0.17	-0.49	1.00			
Intangible K	0.13	-0.22	-0.08	-0.40	0.61	1.00		
Knowledge K	0.08	-0.12	-0.14	-0.46	0.88	0.72	1.00	
Organization K	0.11	-0.27	0.05	-0.11	0.04	0.65	0.09	1.00

Panel B: pre-2000 sample

	Markup	Size	BM	ROA	R&D	Int. K	Know. K	Org. K
Markup	1.00							
Size	0.08	1.00						
BM	-0.15	-0.34	1.00					
ROA	0.14	0.33	-0.05	1.00				
R&D	0.14	-0.04	-0.17	-0.42	1.00			
Intangible K	0.14	-0.18	-0.04	-0.30	0.53	1.00		
Knowledge K	0.10	-0.05	-0.15	-0.38	0.90	0.64	1.00	
Organization K	0.13	-0.22	0.07	-0.08	0.04	0.77	0.11	1.00

Panel C: post-2000 sample

	Markup	Size	BM	ROA	R&D	Int. K	Know. K	Org. K
Markup	1.00							
Size	0.12	1.00						
BM	-0.15	-0.38	1.00					
ROA	0.11	0.38	-0.05	1.00				
R&D	0.13	-0.17	-0.19	-0.56	1.00			
Intangible K	0.13	-0.28	-0.14	-0.50	0.69	1.00		
Knowledge K	0.07	-0.21	-0.16	-0.54	0.89	0.79	1.00	
Organization K	0.10	-0.35	0.00	-0.15	0.04	0.53	0.07	1.00

This table reports the cross-sectional correlation between markup and various stock characteristics. All variables are measured on an annual basis and de-meaned each year to remove time effects. Markup is sales divided by the cost of goods sold. Size is the log of market cap. BM is book-to-market ratio. ROA is net income before extraordinary items divided by assets. R&D is R&D expense to the total assets of a firm. Intangible capital is the sum of knowledge capital and organizational capital (all scaled by total assets). Knowledge and organizational capital are from Peters and Taylor (2017) dataset in WRDS. Full sample is from 1962 to 2021.

Table A.2: Alternative measures of value premium and sample periods

Panel A: post-1993 period value premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Quintile spread		Decile spread		HML factor		Intra-industry	
MKT		0.13*		0.25**		-0.06		0.12*
		(1.65)		(2.55)		(-0.86)		(1.81)
Constant	0.01	-0.09	0.05	-0.14	0.08	0.12	0.23	0.14
	(0.06)	(-0.35)	(0.17)	(-0.45)	(0.41)	(0.57)	(1.18)	(0.69)
Observations	342	342	342	342	342	342	342	342
Adjusted R^2	0.000	0.018	0.000	0.044	0.000	0.003	0.000	0.018

Panel B: post-financial-crisis value premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Quintile spread		Decile spread		HML factor		Intra-industry	
MKT		0.40***		0.53***		0.12		0.24**
		(3.26)		(3.49)		(1.23)		(2.06)
Constant	-0.40	-0.89**	-0.58	-1.23**	-0.25	-0.39	-0.36	-0.65*
	(-1.01)	(-2.15)	(-1.16)	(-2.32)	(-0.94)	(-1.24)	(-1.09)	(-1.82)
Observations	132	132	132	132	132	132	132	132
Adjusted R^2	0.000	0.135	0.000	0.147	0.000	0.018	0.000	0.059

Panel C: excluding Covid-19 period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Quintile spread		Decile spread		HML factor		Intra-industry	
MKT		0.31***		0.49***		0.10*		0.24***
		(4.67)		(5.99)		(1.70)		(4.56)
Constant	0.01	-0.18	0.03	-0.27	0.01	-0.05	0.10	-0.06
	(0.02)	(-0.78)	(0.10)	(-0.84)	(0.05)	(-0.27)	(0.46)	(-0.29)
Observations	222	222	222	222	222	222	222	222
Adjusted R^2	0.000	0.127	0.000	0.177	0.000	0.022	0.000	0.109

This table reports the average monthly return and the CAPM alpha of various measures of the value premium in different sample periods. We measure value premium as the difference in returns between the top and bottom book-to-market quintiles in columns 1 and 2, the difference in returns between the top and bottom book-to-market deciles in columns 3 and 4, the Fama-French HML factor in columns 5 and 6, and the intra-industry value premium in columns 7 and 8 (i.e., the difference in returns between top and bottom BM quintiles in each industry and averaged across industries). Panel A reports the average value premium from 1993m7 to 2021m12. Panel B reports the average value premium from 2011m1 to 2021m12. Panel C reports the average value premium from 2001m7 to 2019m12. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.3: Excess returns of book-to-market and markup sorted portfolios

Panel A: pre-2000 period value premium in markup-sorted portfolios

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup	0.35	0.45*	0.58**	0.62**	0.77***	0.42*
	(1.14)	(1.76)	(2.44)	(2.58)	(2.90)	(1.91)
Mid markup	0.34	0.46*	0.63***	0.82***	1.14***	0.80***
	(1.22)	(1.81)	(2.75)	(3.56)	(4.32)	(3.91)
High markup	0.50**	0.61***	0.56**	0.79***	1.28***	0.77***
	(2.08)	(2.69)	(2.53)	(3.23)	(4.31)	(3.41)
High-Low	0.16	0.15	-0.02	0.17	0.51***	0.35
	(1.02)	(1.08)	(-0.14)	(0.97)	(2.97)	(1.53)

Panel B: post-2000 period value premium in markup-sorted portfolios

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup	0.51	0.76***	0.77**	0.70*	1.13**	0.62*
	(1.45)	(2.76)	(2.21)	(1.77)	(2.33)	(1.92)
Mid markup	1.10***	0.88***	0.87**	0.89**	0.85*	-0.25
	(3.02)	(2.67)	(2.42)	(2.36)	(1.71)	(-0.69)
High markup	0.85***	0.78**	0.67**	0.56	0.55	-0.30
	(3.08)	(2.55)	(2.00)	(1.46)	(1.25)	(-0.95)
High-Low	0.35*	0.03	-0.10	-0.14	-0.58*	-0.92***
	(1.85)	(0.13)	(-0.57)	(-0.65)	(-1.91)	(-2.83)

This table presents the average monthly returns of portfolios double-sorted by companies' book-to-market ratios and markup levels. Value premium is the difference in return between high-BM and low-BM portfolios, reported in column 6. Markup is calculated as sales divided by the cost of goods sold. Portfolios are sorted each year. Panel A reports the returns for the pre-2000 period (July 1963 to June 2001), while Panel B presents the returns for the post-2000 period (July 2001 to December 2021). To conserve space, we omit adjusted R-squared values and the number of observations. All t-statistics (in parentheses) are calculated using Newey-West standard errors. Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Table A.4: Average markup and value premium of different industries

Panel A: Change in industry-level markup

VARIABLES	(1) Low-markup industries	(2) High-markup industries	(3) High minus Low
Post-2000	-0.00	0.19***	0.19***
	(-0.58)	(7.01)	(6.91)
Constant	1.23***	1.72***	0.49***
	(279.52)	(94.86)	(26.32)
Observations	60	60	60
Adjusted R^2	-0.010	0.557	0.553

Panel B: Pre-2000 value premium

VARIABLES	(1) Low-markup industries	(2) High-markup industries	(3) High minus Low
Constant	0.57***	0.69***	0.12
	(2.62)	(3.30)	(0.51)
Observations	456	456	456

Panel C: Post-2000 value premium

VARIABLES	(1) Low-markup industries	(2) High-markup industries	(3) High minus Low
Constant	0.58*	-0.30	-0.88**
	(1.76)	(-1.08)	(-2.52)
Observations	246	246	246

This table reports the average markup and value premium of low- and high-markup industries. We sort SIC 2-digit industries into terciles each year based on their industry's markup, measured as total industry sales to total industry cost of goods sold, and define low- and high-markup industries as those in the bottom and top tercile. We then measure the average markup of industries in each group. Panel A regresses the average markup on the post-2000 dummy variable. Panels B and C report the value premium of stocks in each industry-markup tercile. To do so, we also sort firms based on their book-to-market ratio into quintiles independently. Value premium is the return of stocks in the top BM quintile minus the returns of stocks in the bottom BM quintile. Panel B reports the value premium in the pre-2000 period, which is from 1963m7 to 2001m6. Panel C reports the value premium in the post-2000 periods, which is from 2001m7 to 2021m12. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.5: Robustness check on the cross-sectional value premium post 2000

Panel A: sort firms by the markup from De Loecker et al. (2020)

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup	0.61*	0.71**	0.71**	0.81**	1.25**	0.64**
	(1.73)	(2.59)	(2.03)	(2.06)	(2.58)	(1.99)
Mid markup	1.09***	0.84***	0.85**	0.71*	0.55	-0.54
	(3.03)	(2.75)	(2.27)	(1.94)	(1.12)	(-1.51)
High markup	0.82***	0.81**	0.69**	0.60	0.57	-0.26
	(2.98)	(2.58)	(2.08)	(1.56)	(1.30)	(-0.83)
High-Low	0.21	0.09	-0.02	-0.20	-0.68**	-0.89***
	(1.15)	(0.47)	(-0.12)	(-0.97)	(-2.29)	(-2.84)

Panel B: sort firms by the markup that incorporates SG&A

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup	0.57	0.78***	0.74*	0.86**	1.18**	0.62**
	(1.63)	(2.68)	(1.96)	(2.12)	(2.41)	(2.01)
Mid markup	0.92**	0.71**	0.81**	0.78**	1.03**	0.12
	(2.37)	(2.34)	(2.23)	(2.01)	(2.07)	(0.35)
High markup	0.89***	0.87***	0.69**	0.50	0.43	-0.47
	(3.13)	(2.87)	(2.17)	(1.26)	(0.94)	(-1.40)
High-Low	0.33*	0.09	-0.05	-0.35	-0.76**	-1.09***
	(1.72)	(0.45)	(-0.26)	(-1.56)	(-2.28)	(-3.16)

This table reports post-2000 period average return of bm and markup sorted portfolios. In Panel A, based on De Loecker, Eeckhout, and Unger (2020), the markup of a firm is computed as the estimated cost elasticity, θ, times a firm's sales, $SALE$, and divided by its cost of goods sold, $COGS$. We obtain the cost elasticity from De Loecker's website. In Panel B, we use an alternative definition to measure markup. Our alternative definition includes additional SG&A cost in marginal costs. Specifically, we define alternative markup as

$$Alt\,Markup = \frac{SALE}{COGS + SG\&A - R\&D - ADV}$$

where $COGS$ is cost of goods sold, $SG\&A$ is selling and general admin expense, $R\&D$ is R&D expense (including R&D in progress), and ADV is advertising expense. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.6: Robustness of markup trend under alternative measures

Panel A: measuring markup with cost elasticity

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate markup			Markup terciles		
VARIABLES	EW	AW	SW	Low	Mid	High
Post-2000	0.30***	0.41***	0.21***	0.00	0.08***	0.70***
	(12.71)	(12.56)	(10.11)	(1.07)	(6.75)	(12.94)
Constant	1.49***	1.47***	1.38***	1.08***	1.28***	1.93***
	(69.04)	(117.40)	(112.21)	(456.38)	(271.42)	(54.55)
Observations	60	60	60	60	60	60
Adjusted R^2	0.763	0.869	0.763	0.003	0.640	0.825

Panel B: measuring markup with SG&A expense

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate markup			Markup terciles		
VARIABLES	EW	AW	SW	Low	Mid	High
Post-2000	0.06***	0.14***	0.07***	-0.00	0.04***	0.23***
	(7.88)	(10.20)	(7.45)	(-1.16)	(7.27)	(13.76)
Constant	1.17***	1.28***	1.22***	1.07***	1.17***	1.39***
	(413.90)	(190.96)	(263.25)	(870.28)	(306.58)	(126.31)
Observations	60	60	60	60	60	60
Adjusted R^2	0.703	0.786	0.671	0.021	0.535	0.836

This table conducts additional robustness checks on the trend of the aggregate average markup (equal-weighted, asset-weighted, or sales weighted) and the trend of sales-weighted average markup of different groups of firms using alternative markup measures. In Panel A, based on De Loecker, Eeckhout, and Unger (2020), the markup of a firm is computed as the estimated cost elasticity, θ, times a firm's sales, $SALE$, and divided by its cost of goods sold, $COGS$. We obtain the cost elasticity from De Loecker's website. In Panel B, we measure markup by incorporating parts of the SG&A expense in the marginal cost. Specifically, we define the alternative markup as

$$Alt\,Markup = \frac{SALE}{COGS + SG\&A - R\&D - ADV}$$

where $SG\&A$ is selling and general admin expense, $R\&D$ is R&D expense (including R&D in progress), and ADV is advertising expense. We regress the average markup on the post-2000 dummy variable. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.7: Value premium post 2000, exclude micro-cap or superstars

Panel A: exclude micro-cap stocks

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup	0.52	0.76***	0.77**	0.69*	1.11**	0.60*
	(1.48)	(2.77)	(2.21)	(1.76)	(2.28)	(1.82)
Mid markup	1.10***	0.88***	0.88**	0.88**	0.83*	-0.27
	(3.03)	(2.68)	(2.43)	(2.34)	(1.66)	(-0.72)
High markup	0.85***	0.78**	0.66**	0.54	0.50	-0.35
	(3.08)	(2.55)	(1.98)	(1.42)	(1.13)	(-1.09)
High-Low	0.34*	0.02	-0.11	-0.15	-0.61*	-0.95***
	(1.78)	(0.12)	(-0.59)	(-0.68)	(-1.97)	(-2.83)

Panel B: exclude superstar stocks

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup	0.45	0.79**	0.94**	0.99**	1.02**	0.57*
	(1.09)	(2.09)	(2.28)	(2.27)	(2.03)	(1.89)
Mid markup	0.82**	0.96***	1.00***	0.89**	1.09**	0.27
	(2.35)	(2.81)	(2.67)	(2.17)	(2.23)	(0.89)
High markup	0.94***	0.94***	0.77**	0.49	0.75	-0.19
	(2.98)	(2.90)	(2.04)	(1.17)	(1.55)	(-0.55)
High-Low	0.49**	0.15	-0.17	-0.50**	-0.27	-0.76**
	(2.38)	(0.89)	(-0.93)	(-2.48)	(-1.00)	(-2.30)

This table reports post-2000 period average return of bm and markup sorted portfolios. In Panel A, we exclude micro-cap stocks, which are stocks in the bottom NYSE size decile. In Panel B, we exclude superstar stocks, which are defined as the top 100 firms in terms of sales each year. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.8: Markup of superstar and non-superstar firms

Panel A: average markup of superstar and non-superstar firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Superstar firms			Non-superstar firms		
VARIABLES	EW	AW	SW	EW	AW	SW
Post-2000	0.21***	0.33***	0.13***	0.26***	0.33***	0.20***
	(7.42)	(7.84)	(5.90)	(11.21)	(11.86)	(10.77)
Constant	1.50***	1.59***	1.49***	1.62***	1.62***	1.52***
	(75.42)	(94.04)	(128.31)	(73.98)	(94.53)	(110.43)
Observations	60	60	60	60	60	60
Adjusted R^2	0.591	0.713	0.546	0.706	0.805	0.746

Panel B: average markup of markup-sorted terciles

	(1)	(2)	(3)	(4)	(5)	(6)
	Superstar firms			Non-superstar firms		
VARIABLES	Low	Mid	High	Low	Mid	High
Post-2000	-0.00	0.09***	0.55***	0.01	0.12***	0.52***
	(-0.56)	(8.01)	(9.55)	(1.42)	(9.71)	(10.79)
Constant	1.21***	1.40***	2.13***	1.20***	1.42***	2.07***
	(304.57)	(249.96)	(86.90)	(562.29)	(186.77)	(55.27)
Observations	60	60	60	60	60	60
Adjusted R^2	-0.009	0.652	0.768	0.039	0.734	0.731

This table reports the change of the average markup of superstar and non-superstar firms. Superstar firms are defined as the top 100 firms in terms of sales each year. Panel A reports the change of the equal-weighted (EW), asset-weighted (AW), and sales-weighted (SW) average markup of superstar firms (columns 1 to 3) and non-superstar firms (columns 4 to 6). Panel B reports the change of the sales-weighted average markup of low-, mid-, and high-markup firms within the superstar firms and non-superstar firms. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.9: Value premium and alternative characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-2000				Post-2000			
	Low	Mid	High	H-L	Low	Mid	High	H-L
Panel A: sort by R&D								
Value premium	0.64***	0.53**	0.94***	0.30	0.18	0.15	0.16	-0.02
	(2.90)	(2.06)	(3.26)	(1.11)	(0.54)	(0.46)	(0.49)	(-0.06)
Panel B: sort by ROA								
Value premium	1.00***	0.58***	0.62**	-0.39	-0.20	-0.46	0.32	0.53
	(3.59)	(2.78)	(2.46)	(-1.30)	(-0.57)	(-1.32)	(0.90)	(1.16)
Panel C: sort by intangible capital								
Value premium	0.81***	0.53**	0.57**	-0.25	-0.15	0.08	0.07	0.22
	(3.74)	(2.58)	(2.45)	(-0.95)	(-0.39)	(0.24)	(0.20)	(0.52)
Panel D: sort by knowledge capital								
Value premium	0.66***	0.45**	0.63***	-0.03	-0.01	0.24	-0.01	-0.00
	(3.62)	(2.11)	(2.70)	(-0.15)	(-0.03)	(0.75)	(-0.03)	(-0.00)
Panel E: sort by organizational capital								
Value premium	0.65***	0.58**	0.55**	-0.09	-0.17	0.16	0.28	0.45
	(3.14)	(2.58)	(2.31)	(-0.38)	(-0.52)	(0.49)	(0.67)	(1.06)

This table reports the value premium in different characteristic sorted portfolios in pre-2000 and post-2000 period. In each panel, we double-sort stocks based on book-to-market and a stock characteristic. Value premium is the difference in return between stocks in the top bm quintile and stocks in the bottom bm quintile within each characteristic tercile. Columns 1 to 4 report pre-2000 period result, which is from 1963m7 to 2001m6, and columns 5 to 8 report post-2000 period, which is from 2001m7 to 2021m12. ROA is net income before extraordinary items divided by assets. R&D is R&D expense to the total assets of a firm. Intangible capital is the sum of knowledge capital and organizational capital (all scaled by total assets). Knowledge and organizational capital are from Peters and Taylor (2017) dataset in WRDS. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.10: Intangible-augmented value factor

	(1)	(2)	(3)	(4)
		HML^{INT}		
VARIABLES	Pre-2000 period	Post-2000 period	Full sample	
HML^{FF}			0.53***	
			(20.07)	
HML^{IME}				0.98***
				(47.00)
Constant	0.60***	0.30**	0.35***	-0.01
	(5.01)	(2.14)	(6.52)	(-0.42)
Observations	318	246	564	564
Adjusted R^2	0.000	0.000	0.604	0.853

This table reports the premium of the intangible-augmented value factor, HML^{INT}, in the pre- and post-2000 period. The data is available from Andrea Eisfeldt's website with the first observation in 1975. The pre-2000 period is from 1975m1 to 2001m6 and the post-2000 period is from 2001m7 to 2021m12. The HML^{INT} factor sorts firms based on the ratio between the augmented book value (book equity plus intangible assets) and market value and takes long (short) positions in firms with high (low) ratios. The HML^{IME} factor sorts firms based on the ratio between the intangible assets and market value and takes long (short) positions in firms with high (low) ratios. The value of intangible assets is computed as the accumulated SG&A expenses based on the perpetual inventory method. Details of these factors can be found in Eisfeldt, Kim, and Papanikolaou (2022). HML^{FF} is the Fama and French (1993) value factor. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.11: Change in markup, excluding new firms

Panel A: change in markup of firms more than 3 years old

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate markup			Markup terciles		
VARIABLES	EW	AW	SW	Low	Mid	High
Post-2000	0.25***	0.31***	0.15***	-0.00	0.10***	0.50***
	(10.64)	(10.29)	(7.71)	(-0.07)	(9.02)	(11.10)
Constant	1.59***	1.59***	1.50***	1.21***	1.41***	2.10***
	(72.03)	(124.88)	(119.96)	(372.44)	(208.25)	(71.00)
Observations	57	57	57	57	57	57
Adjusted R^2	0.712	0.811	0.650	-0.018	0.710	0.789

Panel B: change in markup of firms more than 5 years old

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate markup			Markup terciles		
VARIABLES	EW	AW	SW	Low	Mid	High
Post-2000	0.25***	0.32***	0.14***	0.00	0.10***	0.48***
	(10.33)	(10.04)	(7.31)	(0.16)	(8.66)	(10.94)
Constant	1.58***	1.58***	1.50***	1.21***	1.41***	2.10***
	(71.58)	(126.31)	(116.57)	(354.88)	(198.45)	(69.95)
Observations	55	55	55	55	55	55
Adjusted R^2	0.723	0.812	0.639	-0.018	0.700	0.789

Panel C: change in markup of firms more than 10 years old

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate markup			Markup terciles		
VARIABLES	EW	AW	SW	Low	Mid	High
Post-2000	0.23***	0.31***	0.14***	0.00	0.09***	0.45***
	(9.62)	(9.51)	(6.48)	(0.81)	(7.84)	(9.77)
Constant	1.56***	1.57***	1.50***	1.21***	1.42***	2.11***
	(75.87)	(110.02)	(104.29)	(304.08)	(178.11)	(66.00)
Observations	50	50	50	50	50	50
Adjusted R^2	0.745	0.797	0.609	-0.001	0.678	0.770

This table reports the change in aggregate markup in the economy, excluding firms newly entered our dataset. We excluded firms that are less than 3 years old, 5 years old, or 10 years old in Panels A, B, and C. We proxy a firm's age based on the year it entered our dataset. In each panel, columns 1, 2, and 3 report the change of the average markup of all firms with equal-weighted, asset-weighted, and sales-weighted averages, respectively. Columns 4, 5, and 6 report the change of the sales-weighted average markups of firms in the low-, mid-, and high-markup terciles. All t-statistics (in parentheses) are based on Newey-West standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A.12: Value premium and interest rates changes

Panel A: value premium and changes in the short-term treasury yield

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Value premium measured over different horizons							
	Monthly		Annual		5 years		10 years	
VARIABLES	Avg. VP	ΔVP	Avg. VP	ΔVP	Avg. VP	ΔVP	Avg. VP	ΔVP
$\Delta Tbill$	-0.21	0.02	0.07	0.13	-0.02	-0.11	0.13	0.18
	(-1.10)	(0.07)	(0.57)	(0.70)	(-0.17)	(-0.88)	(1.21)	(1.57)
Constant	0.29**	0.00	0.28	-0.03	0.25	-0.13	0.40	0.02
	(2.07)	(0.02)	(1.57)	(-0.13)	(1.23)	(-0.56)	(1.58)	(0.06)
Obs.	701	701	58	58	11	11	5	5
Adjusted R^2	0.000	-0.001	-0.012	-0.009	-0.108	-0.022	0.102	0.270

Panel B: value premium and changes in the long-term treasury yield

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Value premium measured over different horizons							
	Monthly		Annual		5 years		10 years	
VARIABLES	Avg. VP	ΔVP	Avg. VP	ΔVP	Avg. VP	ΔVP	Avg. VP	ΔVP
$\Delta TenYear$	0.61	-0.76	0.17	0.10	0.06	-0.07	0.14	0.17
	(1.22)	(-1.16)	(0.89)	(0.39)	(0.53)	(-0.52)	(1.65)	(1.63)
Constant	0.29**	0.00	0.28	-0.04	0.27	-0.13	0.40	-0.01
	(2.10)	(0.00)	(1.59)	(-0.14)	(1.34)	(-0.51)	(1.81)	(-0.03)
Obs.	701	701	58	58	11	11	5	5
Adjusted R^2	0.001	0.001	-0.004	-0.015	-0.078	-0.079	0.299	0.294

This table reports the relationship between the value premium and changes in interest rates across different horizons. We measure the value premium as the average return difference between the top and bottom BM quintiles over a given time period. The y-variables are the average value premium (in columns 1, 3, 5, 7) or changes in value premium (in columns 2, 4, 6, 8). The x-variables are the change in the average monthly treasury yield in Panel A and the change in the average 10-year treasury yield in Panel B. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.