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

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Abstract

This paper examines how technology adoption and market power jointly explain two significant macroeconomic trends in recent decades: the decline of the value premium and the rise of markups. Empirically, we demonstrate that these trends are predominantly concentrated among high-markup firms, whereas both the value premium and markups remain stable for firms with low markups. To rationalize these patterns, we develop a dynamic monopolistic competition model with endogenous technology adoption and strategic interactions. Our analysis highlights that the observed trends—and their cross-sectional divergence between high- and low-markup firms—emerge from two critical mechanisms: (1) the rising efficiency of the aggregate technology frontier over time, and (2) firm heterogeneity in technology adoption decisions and demand elasticity. The model replicates the empirical dynamics of markups and the value premium, underscoring the interplay between technological evolution and market structure.

Keywords: value premium; markup; technology adoption; technology frontier shocks

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1 Introduction

Recent studies document two significant macroeconomic shifts of past decades: a persistent decline in the value premium and a concurrent rise in markups (Fama and French, 2021; De Loecker, Eeckhout, and Unger, 2020). While the decline in the value premium reflects changing dynamics in financial markets, the rising markups has been linked to structural transformations in industry competition and firm behavior. This paper bridges these phenomena by proposing a unified explanation linking both trends to shifts in market structure, driven by heterogeneous technology adoptions and market power. Empirically, we show that the decline in the value premium and the rise in markups are concentrated among high-markup firms. In contrast, low-markup firms have seen no change in either their value premium or markup levels. We develop a dynamic monopolistic competition model featuring endogenous technology adoption and strategic competitive behavior 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 secular decline in the value premium, the rise in markups, and their difference across firms.

We start off by documenting a decline of the value premium in the past few decades. Consistent with Fama and French (2021), the spread between high and low book-to-market quintile portfolios falls significantly from 5.8% in 1963-2001 to -0.7% in 2001-2021. Similarly, the CAPM alpha of the value premium also decreases substantially from 6.6% to -3.7%. The decline of the value premium is also robust to alternative time cutoff and other measures of the value investing, for instance, the HML factor exhibits a similar decline.

We demonstrate that the decline of the value premium is driven primarily by high-markup firms. For these firms, the value premium fell from 9.2% in 1963-2001 to -3.6% in 2001-2021. In contrast, low-markup firms maintained a stable value premium, fluctuating between 5% and 7.4% over the same periods. Notably, the same high markup firms also exhibit significant increases in their markups over this period from 2.1 in 1963-2001 to 2.6

in 2001-2021, whereas those of low markup firms remain unchanged at around 1.2.[1] These patterns collectively contribute to an overall increase in the aggregate markup from 1.5 in 1963-2001 to 1.7 in 2001-2021.

The empirical evidence suggests a strong link between rising markups and the decline of the value premium. To understand the economic mechanisms behind this relationship, we develop a dynamic monopolistic competitive equilibrium model with three key features: (i) a stochastic aggregate technology frontier fluctuates over time, capturing changes in advanced technologies, (ii) costly technology adoption by firms, and (iii) strategic interactions among firms. In the model, firms can upgrade their technology by adopting the latest technology, albeit at a fixed cost. The benefit of adopting new technology is that it increases production efficiency by reducing the marginal production costs. This efficiency improvement captures the fact that new technologiesas artificial intelligence, Information, Communications and Telecommunications (ICT), cloud storage and computing, automation, etc.,—enable firms to expand into multiple product lines or markets, thereby lowering the marginal production cost in production as the new technologies are non-rival and scalable (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023; Hsieh and Rossi-Hansberg, 2023). Furthermore, firms consider expectations about their own and their competitors' states, e.g., market structure, which influence product market competition and the efficacy of technology adoptions.

We first calibrate the model to capture the pre-2000 economy and show that it produces an aggregate markup at 1.56 close to the data due to a moderate elasticity of demand and marginal production costs. Furthermore, the model also produces a sizable value premium close to the data. In the model, value firms are low productivity firms lagging the technology frontier but cannot catch up with the latest technology due to the adoption cost. As a result, their future cash-flows are more affected by the changes in the aggregate technology frontier and hence are more exposed to the frontier shock than growth firms. Additionally, the model also generates significant CAPM alphas for the value premium, as the cross-

[1]This is consistent with De Loecker, Eeckhout, and Unger (2020) who also showed that the average markup comes mostly from the firms with markups above the median markups.

sectional risk dispersion in the model is driven primarily by exposures to aggregate technology frontier shocks, whereas the market return is driven more by both aggregate technology and productivity shocks.

To study the post-2000 economy, we highlight heterogeneities over time and across high and low markup groups of firms. We first assume a significant increase in the efficiency of the technology frontier (long-run average) compared to the pre-2000 economy. This captures advancements in technologies including that have broadly impacted firms since the late 1990s by reducing firms' production costs as in Aghion, Bergeaud, Boppart, Klenow, and Li (2023). Second, we assume heterogeneities between low- and high-markup firms in three key dimensions: (i) the marginal production costs which determines the benefits of technology adoption and the costs of technology adoption, (ii) firms' demand elasticity which reflects market power, and (iii) fixed operating costs. Third, there is within-group heterogeneity in firm-specific productivity that leads to dispersion in firm-level risk.

To examine heterogeneities in the high and low markup groups, we calibrate the model using key firm-level moments including average markup, technology adoption rate, fixed costs to sales ratio, and net income to sales ratio in each group. The calibration reveals that high-markup firms exhibit significantly lower marginal production costs and demand elasticity. In the model, marginal production costs and adoption benefits are inversely related, consequently, high markup firms have greater adoption benefits relative to adoption costs, resulting in higher adoption rates. Lower demand elasticity reflects higher market power, together with lower marginal production costs, translate into higher markups for these firms. Turning to the value premium, due to low production costs relative to revenue for high markup firms, the impact of the frontier technology shocks is similar across firms in the group. Hence value and growth firms have similar exposure to technology frontier shocks, leading to a near-zero value premium. In contrast, low-markup firms face higher marginal production costs and greater demand elasticity, resulting in lower adoption rates and small markups. Moreover, high production costs relative to revenue make value firms

(those with low productivity) firms more exposed to technology frontier shocks than growth firms within the low markup firms. This occurs because value firms, being less productive and lagging behind the frontier, are less able to adopt new technology as the benefits not outweighing the adoption costs, which leads to a sizable value premium.

We conduct several counterfactual analyses to understand the model mechanisms. First, we increase the efficiency of the aggregate technology frontier in the post-2000 economy by 50% relative to the baseline calibration. As a result, the markups of both high-markup and low-markup firms become counterfactually too large, while the value premium of low-markup firms drops to zero. Second, we analyze the impact of cross-group heterogeneities by eliminating them one at a time. Our findings show that heterogeneity in marginal production costs (reflecting the benefits of technology adoption) and demand elasticity (capturing firms' market power) play a first-order role in driving variations in markups and the value premium between low- and high-markup firms. Specifically, eliminating heterogeneity in both margins significantly reduces the markup and value premium differences between low- and high-markup firms relative to the baseline, leading to a substantial decline in the value premium of low-markup firms and a sharp rise in their markups. In contrast, removing heterogeneity in technology adoption costs or fixed operating costs only affect technology adoption rates and dividend payout but does not have a significant impact on the markup or the value premium. Lastly, while the risk prices of aggregate productivity shocks and technology frontier shocks significantly influence the value premium —with the risk price of the frontier shock having the predominant effect —these changes do not have a notable impact on markups.

Furthermore, the model highlights a unique channel that contributes to the slowdown in total factor productivity (TFP) growth observed over the past several decades (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023; De Loecker, Eeckhout, and Unger, 2020; De Ridder, 2024). When low-markup firms in the model are assumed to have the same (low) marginal production costs as high-markup firms, the measured aggregate TFP —which reflects capital misallocation within these groups —increases by 1.3% relative to the baseline

calibration. Conversely, when low-markup firms are assigned the same (low) firm demand elasticity, i.e., the same market power, the measured aggregate TFP falls by 0.7%, compared to the baseline calibration. These findings suggest that a key driver of sluggish TFP growth is the combination of high marginal production costs among low-markup firms and strong market power among high-markup firms. Together, these factors exacerbate capital misallocation, impeding overall productivity growth. This result has potential policy implications. In particular, 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 for high-markup firms)—could mitigate misallocation and revitalize productivity growth.

Lastly, to capture the strategic interactions in the model, we focus our analysis on the Markov perfect equilibrium (MPE) as outlined by Ericson and Pakes (1995). To address the significant computational challenges associated with MPE —particularly when dealing with a large number of firms —we adopt the concept of oblivious equilibrium proposed by Weintraub, Benkard, and Van Roy (2008). In this framework, firms base their decisions on a belief about the long-term average industry structure rather than the specific states of competitors. As a result, strategic interactions occur through the industry state in our model, which is represented by aggregate capital. In the model, a high level of aggregate capital is associated with lower aggregate prices, reflecting increased price pressure as competitors undercut prices. Interestingly, these strategic interactions yield distinct implications for firms' physical investment and technology adoption strategies. While higher aggregate prices lead to reduced investment due to a decrease in marginal product of revenue, they also lead to greater technology adoption. The latter occurs because lower marginal production costs by adoption counteract the effects of higher aggregate prices.

Furthermore, the aggregate price elasticity, which determines the strength of strategic interactions, quantitatively influences the model results. When strategic interactions weaken (i.e., when aggregate demand elasticity is higher), the value premium for low-markup firms

declines sharply. This occurs because as industry prices become less responsive to aggregate shocks, firms' exposure to frontier shocks converges, reducing within-industry risk dispersion and, consequently, lowering the value premium. Additionally, the adoption rate and net income-to-sales ratio for low-markup firms increase significantly, while these variables exhibit only a slight increase for high-markup firms.

Literature review This paper relates to a few strands of literature. The first is the growing literature that explores recent macroeconomic trends, including the rise of aggregate markup, the decline of aggregate TFP growth and business dynamism. De Loecker, Eeckhout, and Unger (2020) document a substantial increase in the aggregate markup during over the recent decades. Aghion, Bergeaud, Boppart, Klenow, and Li (2023), Hsieh and Rossi-Hansberg (2023), De Ridder (2024), among others highlighted the significant role of technological changes in driving this increase in the aggregate markup, whereas Akcigit and Ates (2021) and Olmstead-Rumsey (2022) link these trends to a slowdown in imitation rates and a decline innovation efficiency, respectively. We distinguish from these studies by connecting the rise in aggregate markup to changes in asset prices through the decline of the value premium, with both trends being driven by high markup firms. Furthermore, our analysis points to technology as a driver, but emphasizes firm heterogeneity in shaping the cross-sectional variations in these trends.

The paper also relates to the recent studies on the decline of the value premium. Fama and French (2021) document a substantial decline in the value premium over the last few decades. Several studies, such as those by Park et al. (2019), Arnott, Harvey, Kalesnik, and Linnainmaa (2021), Eisfeldt, Kim, and Papanikolaou (2022), and Gulen, Li, Peters, and Zekhnini (2021), suggest that the decline can be attributed to traditional book-to-market ratios not including intangible assets, while Gonçalves and Leonard (2023) associate the decline in the value premium with the measurement of firms' fundamental equity. Unlike these studies, we link this decline to rising markups, demonstrating that it is primarily driven by firms with high markups. We further quantify this effect in a monopolistic competitive

equilibrium model with technology adoption, thus providing a comprehensive analysis of the underlying mechanisms.

Our paper contributes to the growing literature exploring how market structure influences industry dynamics and asset prices. Bustamante (2015) and Bustamante and Donangelo (2017) , Loualiche (2021), and Corhay, Kung, and Schmid (2020) focus on the interactions between product market competition and expected stock returns, while Corhay (2017) examines the links between industry competition and credit spreads. Dou, Ji, and Wu (2021, 2022) investigate the implications of strategic competition in dynamic games, Chen, Dou, Guo, and Ji (2023) examine how firms' strategic competition in financial distress, while Corhay, Kung, and Schmid (2025) study the connections between polarization in Tobin's Q, markup and the rise of superstar firms. Our paper differs from these studies in two significant ways. Empirically, we uncover a novel link between markup trends and cross-sectional returns, bridging recent macroeconomic trends with asset pricing. Theoretically, we analyze a monopolistic competitive equilibrium featuring rich heterogeneity across firms and groups. This framework enables us to examine both the value premium and its variations across firms with differing markups.

Furthermore, our paper also relates to the literature exploring the connections between technological changes, the macroeconomy, and financial markets. Prior studies, such as Papanikolaou (2011), Kogan and Papanikolaou (2014), and Garlappi and Song (2017), have examined the asset pricing implications of investment-specific technological changes. In contrast, we build on the broad literature investigating the economic impacts of shifts in the aggregate technology frontier, including works by Parente and Prescott (1994), Greenwood and Yorukoglu (1997), Cooper, Haltiwanger, and Power (1999), and more recent analyses by Lin, Palazzo, and Yang (2020). Moreover, our model incorporates endogenous technology adoption, investment decisions and strategic interactions among firms. This framework allows us to investigate the underlying drivers linking the decline of the value premium to the rise of markups.

Lastly, our model connects to the recent industrial organization (IO) literature on industry structure dynamics within the context of strategic competition, particularly in dynamic games. Foundational studies by Maskin and Tirole (1988a,b) and Ericson and Pakes (1995) introduce the concept of Markov Perfect Equilibrium (MPE) and examine the implications for equilibrium conditions in industry dynamic model. Building on this foundation, Weintraub, Benkard, and Van Roy (2008) work out an MPE model where firms track only their own states and the overall industry state to capture strategic competition. Expanding on these works, our study is among the first to investigate the asset pricing implications of an MPE model (within the Ericson and Pakes framework) in a monopolistic competitive industry featuring endogenous technology adoption.

The paper proceeds as follows. Section 2 shows the empirical links between the trend of markups and the value premium. Section 3 presents the model. Section 4 presents the quantitative 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. First, we document the decline of the value premium alongside the rise of markups in the aggregate economy. Next, we demonstrate that firms with higher markups experience larger declines in their value premium and greater increases in markups. In contrast, firms with low markups exhibit stable value premiums and markups throughout the whole sample period. Finally, we perform robustness checks.

2.1 Data

We collect data from several sources. Stock return and market capitalization are from CRSP. Accounting information is from Compustat. We download factor returns and returns on book-to-market (BM) sorted portfolios from Ken French's website.[2] We also obtain data on intangible assets from the Peters and Taylor (2017) dataset through WRDS. We download the cleaned text data of 10-K filings from Loughran-McDonald website for textual analysis in Section 6.2.[3]

2.2 The decline of the value premium

This section documents the decline of the value premium since the turn of the century. Table 1 presents various measures that illustrate this decline, including the value-minus-growth quintile and decile spreads and the HML factor.

Panel A in Table 1 reports the average excess return and the CAPM alpha of the value-minus-growth quintile portfolio, the value-minus-growth decile portfolios, and the he Fama and French (1993) HML factor from July 1963 to June 2001, which we label the pre-2000 period. During this period, value stocks consistently outperform growth stocks. For instance, the value-minus-growth long-short quintile portfolio return is 0.48% per month with a t-statistic of 2.55. The CAPM alpha of this return spread is 0.55% per month with a t-statistic of 2.93. Similarly, the average return and the CAPM alpha of the value-minus-growth decile portfolio is 0.58% and 0.64% per month, respectively. The average HML factor return is 0.45% per month with a t-statistic of 2.81.

Panel B in Table 1 presents the performance of the value premium during the post-2000 period, spanning July 2001 to December 2021. Over this 20-year period, the value premium has effectively disappeared, as evidenced by both the average excess return and the CAPM alpha, which no longer exhibit significant positive values. For instance, the value-minus-

[2]Link to the website is https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
[3]Link to the website is at: https://sraf.nd.edu/sec-edgar-data/

growth quintile and decile spreads are −0.06% and −0.07% per month, respectively, while the average return of the HML factor is −0.05% per month. The corresponding CAPM alphas are also negative. Overall, Table 1 highlights a significant decline in the value premium over the past 20 years. Additionally, Figure 1 plots the 20-year rolling average return of the value-minus-growth quintile portfolio and the HML factor. The figure reveals a clear and steady decline in the value premium over time.

2.3 The rise of markups

Another important macroeconomic trend as documented by De Loecker, Eeckhout, and Unger (2020) is the rapid increase in the aggregate markup. 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 revenue to the cost of goods sold.[4] Figure 2 displays the aggregate markup (revenue-weighted average) in the economy from 1963 to 2021. The average markup remained around 1.45 during the 1960s and 1970s but began to rise in the 1980s, reaching 1.77 in 2021–a 25% increase from its historical low. Similar trends are observed using alternative measures of markup. Panel A of Table 2 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 revenue-weighted average markup increases from 1.50 to 1.66.

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

[4] De Loecker, Eeckhout, and Unger (2020) measure a firm's markup as the ratio of its revenue to the cost of goods sold, adjusted by an estimated industry demand elasticity coefficient. They employ several approaches to estimate this elasticity across industries, with the estimated interquartile range from 0.84 to 0.92. Our approach is directly based on the model and does not rely on the estimated demand elasticity, as the production cost is explicitly specified in our model. Nevertheless, we demonstrate that incorporating the estimated demand elasticity coefficient into the markup calculation does not alter our findings.

firms. This pattern is detailed in Panel B of Table 2. In this panel, firms are sorted into three terciles based on their markups from the prior year, and the revenue-weighted average markup for each group is calculated for the current year. Column 1 shows that the average markup of firms in the bottom tercile remains stable over time. Column 2 indicates that firms in the mid-markup tercile experience a modest increase in average markup, rising by 0.10 from 1.41 before 2000 to 1.51 after 2000, a 7% increase. Column 3 reveals that high-markup firms see the most substantial rise, with their average markup increasing by 0.54 from 2.10 before 2000 to 2.64 after 2000, representing a 26% increase. Figure 3 provides a time series plot of the average markups for low-markup and high-markup firms from 1963 to 2021. 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 .

2.4 Linking the two trends

Is the decline of the value premium driven by the rise in markups? To explore this question, we first sort firms into three terciles based on their individual markups. [5] Next, we independently sort firms into quintiles based on their book-to-market ratios, creating 15 portfolios. The value premium is then calculated as the return spread between the high book-to-market and low book-to-market quintiles. Our analysis reveals that the decline in the value premium is concentrated among high-markup firms, while the value premium for low-markup firms remains stable over time.

Panel A of Table 3 presents the average returns for the 15 portfolios and the long-short portfolios during the pre-2000 period (July 1963 to June 2001). Across all three markup groups, value stocks consistently outperform growth stocks. The high-minus-low spreads are 0.44%, 0.80%, and 0.77% per month for low-markup, mid-markup, and high-markup firms, respectively. Furthermore, the difference in the value premium between low-markup and high-markup firms is not statistically significant during this early period, indicating a robust

[5] Sorting firms by industry markup yields similar results.

value premium across markup levels.

Panel B of Table 3 reports the average returns for the post-2000 period (July 2001 to December 2021). During this later period, value stocks exhibit significantly higher average returns than growth stocks only within the low-markup tercile. Specifically, value stocks in the low-markup tercile outperform growth stocks by 0.62% per month, with a t-statistic of 1.91. In contrast, value stocks in the mid-markup and high-markup terciles *underperform* growth stocks by 0.25% and 0.30% per month, respectively, although these differences are not statistically significant. Notably, the value premium of high-markup firms is significantly lower than that of low-markup firms, with a difference of -0.92% per month and a t-statistic of -2.74. Furthermore, Table A.3 in the Online Appendix shows that the CAPM alphas of these double-sorted portfolios follow a similar pattern, reinforcing the findings.

Table 4 analyzes changes in the value premium for low- and high-markup terciles before and after 2000. To estimate these changes, we regress the monthly value-minus-growth quintile returns for each tercile on a post-2000 dummy variable. Columns 1 and 4 reveal that the value premium for low-markup firms, both in terms of average returns and CAPM alphas, remains statistically unchanged in the post-2000 period. In contrast, Columns 2 and 5 show that the value premium for high-markup firms declined by over 1% per month in the post-2000 period. Columns 3 and 6 further examine the difference in the value premium between high- and low-markup terciles, revealing that the decline in the value premium is significantly more pronounced for high-markup firms than for low-markup firms. Overall, the results highlight that the decline in the value premium is predominantly driven by firms with high markups, while the value premium for low-markup firms has remained stable over time.

2.5 Robustness checks

To check the robustness of our main findings, we conducted 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 conclusions here.

Alternative sample period cutoffs We first examine whether the decline in the value premium depends on the choice of sample period cutoffs. In the Appendix, Table A.1 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. Similar patterns are observed for the Fama and French (1993) HML factor returns. These findings demonstrate that the decline in the value premium is robust to variations in the sample period cutoffs.

Alternative measures of markups Another robustness check evaluates whether the link between the decline in the value premium and rising markups holds when using alternative measures of markup. Following De Loecker, Eeckhout, and Unger (2020), our baseline definition of markup is the ratio of revenue to a firm's cost of goods sold, which assumes that cost of goods sold measures variable costs. Alternatively, we define markup as revenue divided by the sum of the cost of goods sold and SG&A costs, excluding R&D and advertising expenses—effectively incorporating more costs into the measurement of variable costs. Appendix Table A.5 demonstrates that in the post-2000 period, the value premium remains positive and significant among firms with low markups under the alternative definition. In contrast, the value premium among firms with high alternative markups is not statistically significant.

Additionally, we measure a firm's markup at the industry level, defined as industry-level revenue divided by industry-level cost of goods sold. Table A.4 of the online appendix presents the results. Consistent with our main findings, firms in low-markup industries exhibit a significant value premium in the post-2000 period, while the value premium among firms in mid- and high-markup industries becomes insignificant. Furthermore, while the difference in the value premium between low-markup and high-markup industries is insignif-

icant in the pre-2000 period, it is significant in the post-2000 period. These results confirm that the connection between the decline in the value premium and rising markups is robust to alternative measures of markup.

Intra-industry value premium The literature has emphasized that the value premium is more pronounced when measured within industries (Cohen and Polk (1998),Novy-Marx (2011)). We confirm that the intra-industry value premium has also declined significantly, as shown in Table A.2. To calculate the intra-industry value premium, we first compute the value premium (the return difference between stocks in the top and bottom book-to-market quintiles) within each of the Fama-French 30 industries and then average these premiums across industries, using total industry market capitalization as weights. Columns 1 and 2 of Table A.2 demonstrate that the intra-industry value premium was highly significant in the pre-2000 period, both in terms of average return and CAPM alpha. Furthermore, Columns 3 and 4 show that in the post-2000 period, the intra-industry value premium has effectively disappeared, with values that are not significantly different from zero.

Excluding micro-cap stocks We also assess whether our cross-sectional findings on the decline of the value premium are influenced by micro-cap stocks. To do so, we exclude stocks in the bottom NYSE size decile from our sample and re-estimate the value premium across different markup terciles for the post-2000 period. Appendix Table A.5, Panel B, presents the results. The value premium in the low-markup tercile remains positive and significant at 0.6% per month with a t-statistic of 1.83, while the value premium in the high-markup tercile is -0.35% per month with a t-statistic of -1.02. These results align closely with our baseline findings, confirming that the observed patterns are not driven by micro-cap stocks.

Excluding superstar firms We investigate whether the decline in the value premium and the increase in markups are driven by superstar firms, as Autor, Dorn, Katz, Patterson, and Van Reenen (2020) suggest that superstar firms - the largest firms in the economy - have played a significant role in recent macroeconomic trends, including the decline in the labor share. While it is true that the markups of superstar firms have increased, we demonstrate

that this channel does not drive our findings. Specifically, we exclude the largest firms from our sample and re-estimate our main empirical tests. The results remain consistent with our baseline findings, as shown in Appendix Table A.6.

Relationships with other characteristics Finally, we test whether other key firm characteristics —such as size, profitability, R&D expenses, and various types of intangible assets —explain our findings. First, as shown in Appendix Table A.7, the correlations between markups and these characteristics are generally small, typically less than 10%. More importantly, we examine the value premium within portfolios sorted by these characteristics. In the pre-2000 period, the value premium is almost always significant within these characteristic-sorted portfolios. However, in the post-2000 period, none of these portfolios exhibits a significant value premium. Appendix Table A.8 presents these results, indicating that the decline in the value premium is consistent across firms with varying size, profitability, R&D expenses, and intangible assets.

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 strategic competition. Moreover, we allow for several sources of heterogeneities in the model: the first is the cross-time difference in the efficiency of the aggregate technology frontier, the second is differences in the benefit (the marginal production cost) and cost of frontier technology adoption, demand elasticity and fixed operating costs across low- and high-markup groups, and the last is firm-specific productivity within each group.

The cross-time heterogeneity captures the fact that aggregate technology has advanced drastically since the late 1990s. This includes widespread adoption of information technology, artificial intelligence, automation, etc., which have significantly improved the production efficiency (Aghion, Bergeaud, Boppart, Klenow, and Li (2023); Hsieh and Rossi-Hansberg (2023)). Cross-group heterogeneities capture the variation in the benefits firms gain by reducing the marginal production costs and the costs they incur when adopting new technologies, which can be attributed to the match between new technology and organizational structures, and the differences in firms' market power. Firm-specific productivity generates firm-level heterogeneity. We identify cross-time and cross-group heterogeneities by using both asset pricing and quantity moments across firms and over time. Strategic interactions arise in the model because the aggregate price is influenced by the strategies of all competitors, which, in turn, affect firms' demand by changing the marginal product of revenue.

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 produces a differentiated product ($y_{j,t}$) and faces a demand function:

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

where $y_{j,t}$ is firms' output and $p_{j,t}$ is the price that firms set, while Q_t and P_t are the aggregate industry output and price index.[6] The parameter ξ controls the elasticity of substitution between different products. This demand function is consistent with Dixit and Stiglitz (1977) who characterize the structure of the standard monopolistic competition model, and is also used in the literature, e.g., Aw, Roberts, and Xu (2011), Corhay, Kung, and Schmid (2020) among others.

Furthermore, we assume that the aggregate industry output faces an isoelastic demand

[6]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.

curve with

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

where η is the the constant elasticity of the industry demand. From equation (1), it implies that the output of firm j is given by

$$y_{j,t} = \frac{P_t^{\xi-\eta}}{p_{j,t}^{\xi}}, \tag{3}$$

where the demand elasticity of substitution across products within an industry is higher 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 the output. The production function exhibits constant returns to scale given by

$$y_{j,t} = X_t z_{j,t} k_{j,t}, \tag{4}$$

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

$$\log(X_{t+1}) = \rho_x \log(X_t) + \sigma_x \varepsilon_{t+1}^X, \tag{5}$$

$$\log(z_{j,t+1}) = \rho_z \log(z_{j,t}) + \sigma_z \varepsilon_{j,t+1}^z, \tag{6}$$

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 the demand function and the production function together, we get the firm's

revenue function:

$$rev_{j,t} = y_{j,t} p_{j,t} = P_t^{1-\frac{\eta}{\xi}} \left(X_t z_{j,t} k_{j,t}\right)^{1-\frac{1}{\xi}}. \tag{7}$$

Physical capital accumulation is given by

$$k_{j,t+1} = (1 - \delta_k) k_{j,t} + i_{j,t}, \tag{8}$$

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

Following Abel and Eberly (1994), Cooper (2005), 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), Parente (1995) and Lin, Palazzo, and Yang (2020), 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, and innovative management practices that enhance firm efficiency. We assume that the stochastic technology frontier S_{t+1} follows the process below:

$$s_{t+1} = (1 - \rho_s) \bar{s} + \rho_s s_t + \sigma_s \varepsilon^s_{t+1}, \tag{9}$$

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 shock, respectively. $\bar{s}$ 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:

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

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

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

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

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

The benefit of adopting the frontier technology is that firms are more efficient with lower marginal production costs, which is 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 given $\frac{f_o}{(1-\delta_n) n_{j,t-1}} y_{j,t}$. Hence

the production costs $oc_{j,t}$ is given by

$$oc_{j,t} = \begin{cases} \frac{f_o}{S_t} y_{j,t}, & \text{if } \phi_{j,t} = 1 \\ \frac{f_o}{(1-\delta_n) n_{j,t-1}} y_{j,t}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{13}$$

This assumption highlights several ways in which new technologies can enhance firm efficiency by reducing the 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)). Secondly, 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)).

3.5 Firms' maximization problem

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

$$d_{j,t} = rev_{j,t} - i_{j,t} - h_{j,t} - oc_{j,t} - ac_{j,t} - f. \tag{14}$$

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:

$$M_{t,t+1} = \exp(-r_f) \frac{\exp(-\gamma_x \triangle x_{t+1} - \gamma_s \triangle s_{t+1})}{E_t[\exp(-\gamma_x \triangle x_{t+1} - \gamma_s \triangle s_{t+1})]} \tag{15}$$

where 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 sign of the risk factor loading parameters

(γ_x and γ_s) is positive, consistent with the evidence reported in the empirical section (we also perform comparative statics to these parameters to understand its importance on the model results). The risk-free rate is set to be constant. This allows us to focus on risk premia as the main driver of the results in the model as well as to avoid parameter proliferation.

We denote the vector of stat 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 $n_{j,t}$, (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 S=$\mathrm{R}_+ \times \mathrm{R}_+ \times \mathrm{R}_+$.

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

$$v_{j,t}\left(\Theta_t\right) = \max_{i_{j,t}, \phi_{j,t}} : \left\{d_{j,t} + E_t\left[M_{t,t+1} v_{j,t+1}\left(\Theta_{t+1}\right)\right]\right\}, \tag{16}$$

subject to the capital accumulation equation (8) and the flow of funds constraint (14) for all dates t given a law of motion for the joint distribution of idiosyncratic productivity, phusical capital and technology capital

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

3.6 Equilibrium

This section first characterizes the equilibrium, then discusses the equilibrium approximation approach and lastly the equilibrium risk and returns.

3.6.1 Monopolistic competitive equilibrium

Monopolistic competitive equilibrium implies that firms take into account the strategies of all other competitors when determining their optimal choices. Building on the founda-

tional work of Maskin and Tirole (1988a) and Ericson and Pakes (1995), we focus on the Markov Perfect Equilibrium. In this framework, the optimal strategies of firms depend on the current states that affect their payoff functions. In the model, firms' strategies include the physical investment strategy $i_{j,t}\left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$, and the technology adoption strategy $\phi_{j,t}\left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$. Then the Markov perfect equilibrium is characterized as the following:

- Each firm chooses optimal strategies $i_{j,t}\left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$ and $\phi_{j,t}\left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$ given the current individual states, aggregate states, and the perceived transitional kernel of the industry state χ_t.
- These perceptions align with the behaviors of each firm's competitors.
- Industry aggregation holds with $Q_t = \left(\int_j y_{j,t}^{\frac{\xi-1}{\xi}} \, dj\right)^{\frac{\xi}{\xi-1}}$ and $Q_t = P_t^{-\eta}$.

To solve the Markov perfect equilibrium model, we need to compute the Markovian transition kernel for the industry state . However this poses significant challenges, as the industry state depends on the optimal strategies of all industry players. This task becomes practically infeasible in the industry equilibrium with many firms. Therefore, we utilize the concept of oblivious equilibrium, developed by Weintraub, Benkard, and Van Roy (2008). Their study shows that in non-concentrated industries with a large number of firms, oblivious strategies-which depend solely on the long-run average industry state-can closely approximate a Markov perfect equilibrium.

Specifically, Weintraub, Benkard, and Van Roy (2008) demonstrate that the industry state forms an ergodic Markov chain when firms' equilibrium strategies depend solely on the long-run industry state. They show that in non-concentrated markets, individual firms gain no advantage from unilaterally deviating to an optimal yet non-obvious strategy by monitoring the true industry state as the long-run average industry state. They show that obvious equilibrium closely approximates the Markov perfect equilibrium where industries have a large number of firms. Our approximation approach assumes that the long-run average

industry state is captured by the aggregate capital $K_t = \int_j k_{j,t} dj$ and approximate the law of motion of K_t and P_t.[7] Appendix B details the numerical procedure of solving the Markov perfect equilibrium.

3.6.2 Equilibrium risk and return

In the model, risk and expected stock returns are determined endogenously along with the firm's optimal investment and financing decisions. To make the link explicit, we can evaluate the value function in equation (16) at the optimum and obtain

$$v_{j,t}(\Theta_t) = d_{j,t} + E_t\left[M_{t,t+1} v_{j,t+1}(\Theta_{t+1})\right] \tag{18}$$

$$\Longrightarrow 1 = E_t\left[M_{t,t+1} r^s_{j,t+1}\right] \tag{19}$$

in which equation (18) is the Bellman equation for the value function, and the Euler equation (19) follows from the standard formula for stock return $r^s_{j,t+1} = v_{j,t+1}(\Theta_{t+1}) / [v_{j,t}(\Theta_t) - d_{j,t}]$. Substituting the stochastic discount from equation (15) into equation (19), and some algebra yields the following equilibrium asset pricing equation:

$$E_t\left[r^e_{j,t+1}\right] = \lambda_x \times \beta^{j,x}_t + \lambda_s \times \beta^{j,s}_t \tag{20}$$

in which $r^e_{j,t+1} = r^s_{j,t+1} - R_f$ is the stock excess return, $\lambda_x = \gamma_x Var(\triangle x_{t+1})$ and $\lambda_s = \gamma_s Var(\triangle s_{t+1})$ are the price of risk of the aggregate productivity shock and aggregate operation cost shock, respectively, and $\beta^{j,x}_t = \frac{Cov\left(r^e_{j,t+1}, \triangle x_{t+1}\right)}{Var(\triangle x_{t+1})}$ and $\beta^{j,s}_t = \frac{Cov\left(r^s_{j,t+1}, \triangle s_{t+1}\right)}{Var(\triangle s_{t+1})}$ are the sensitivity (betas) of the firm's excess stock returns with respect to the two aggregate shocks in the economy.

According to equation (20), the equilibrium risk premiums in the model are determined

[7] Intuitively, aggregate technological capital should also influence the long-run state of an industry. Since firms' decisions to adopt technology are discrete choicesâimplying that those who adopt operate on the frontier S_t, while those who do not depreciate their previously adopted technologyâaggregate technological capital becomes a function of S_t, which itself is already an aggregate state variable for all firms.

by the endogenous covariances of the firm's excess stock returns with the two aggregate shocks (quantity of risk) and its corresponding prices of risk. The sign of the price of risk of the two aggregate shocks is determined by the two factor loading parameters (γ_x and γ_s) in the stochastic discount factor in equation (15). The pre-specified sign of the loadings imply a positive price of risk of both the aggregate productivity shock and the frontier shock. Thus, all else equal, assets with returns that have a high positive covariance with the aggregate productivity shock or the frontier shock are risky and offer high average returns in equilibrium.

3.7 Markups

Following De Loecker, Eeckhout, and Unger (2020), we define firms' markup as the price-marginal cost ratio $\mu_{j,t} = \frac{p_{j,t}}{\frac{\partial\left(oc_{j,t}\right)}{\partial y_{j,t}}}$. From equations (4) and (13), we can show that $\mu_{j,t} = \frac{p_{j,t}}{\frac{\partial\left(oc_{j,t}\right)}{\partial y_{j,t}}} = \frac{p_{j,t}y_{j,t}}{oc_{j,t}}$, which implies that the markup is the share of input expenses as a proportion of total firm's revenues, consistent with De Loecker, Eeckhout, and Unger (2020) and the empirical measure that we use for markup in the data.[8] From equation (3), we find

$$\mu_{j,t} = \begin{cases} \left(z_{j,t}k_{j,t}X_t\right)^{-\frac{1}{\xi}} P_t^{1-\frac{\eta}{\xi}} \frac{S_t}{f_o}, & \text{if } \phi_{j,t} = 1 \\ \left(z_{j,t}k_{j,t}X_t\right)^{-\frac{1}{\xi}} P_t^{1-\frac{\eta}{\xi}} \frac{(1-\delta_n)n_{j,t-1}}{f_o}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{21}$$

From the above equation, markup depends on firms' technology adoption decisions. In particular, the model-implied markup is larger for firms that adopt the frontier technology. This is intuitive, because firms would only adopt the new technology if the technology frontier is more efficient than the current technology capital after depreciation (i.e., $S_t > (1-\delta_n)n_{j,t-1}$), which leads to a smaller marginal cost of production.

[8] In Appendix C, we show how the optimal adoption choice and future firm value affect the firm's markup.

4 Model results

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

4.1 Calibration

To examine the decline of the value premium and the rise in markups since around 2000, we calibrate the model for two distinct economies: the pre-2000 economy and the post-2000 economy. In the pre-2000 economy, we focus on aggregate-level markup and the value premium,[9] while in the post-2000 economy, we emphasize heterogeneities between low- and high-markup groups in driving the two trends. Accordingly, we divide the parameters into two categories: those common to both pre-2000 and post-2000 economies, and those that vary across the two economies and between low- and high-markup groups in the post-2000 economy.

We solve the model at a quarterly frequency and report the parameters in Table 5. 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 400 quarters to neutralize the impact of the initial condition. The remaining 600 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. Because we do not explicitly target the cross section of return spreads (and abnormal returns) in the baseline calibration, we use these moments to evaluate the model in Section 3.

Parameters common across the pre- and post-2000 economies

[9] We do not incorporate heterogenieities for the pre-2000 economy becauess the value premium is not significantly different between low and high markup groups of firms.

Firm's technology. We set the industry demand elasticity $\eta = 4$ and the capital depreciation rate δ_K is set to be 3.5% per quarter as in Bloom (2009). There is no readily available estimate for the depreciation of technology capital δ_n in the data, we set it to 4.5% (18% annually) within the range of empirical estimates of the depreciation rate for intangible capital in the literature.[10]

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 the estimated in Campbell, Lettau, Malkiel, and Xu (2001). We calibrate the subject 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.[11]

Parameters varying across two economies For parameters that vary between the pre- and post-2000 economies, we calibrate them separately for each period. These parameters include the long-run average efficiency of the aggregate technology frontier ($\bar{s}$), which we calibrate by following Aghion, Bergeaud, Boppart, Klenow, and Li (2023), as well as four firm-level parameters: firm demand elasticity (ξ), marginal production costs (f_o), technology adoption costs (f_a), and fixed operating costs (f). Demand elasticity reflects firms' market

[10] 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 intangibel capital including R&D capital.

[11] The positive price of technology frontier risk is supported by the evidence in Baron and Schmidt (2017), who show that consumption rises after an aggregate shock to the technology frontier, and in Jovanovic and Rousseau (2005), who show that consumption rises during the two major eras of technology frontier growth, the Electrification era and the IT era, and in Lin, Palazzo, and Yang (2020) who estimate the price of risk of technology frontier shocks and obtain a positive and significant value.

power, while the marginal production costs (f_o) determines the technology adoption benefit in equilibrium. Intuitively, the lower f_o is, the higher the adoption benefit is for the firm given the technology frontier shock. Technology adoption costs (f_a) directly affects the equilibrium technology adoption rate, while fixed cost (f) affects the dividend-to-sales ratio. Notably, these four firm-level parameters also differ between low- and high-markup groups in the post-2000 economy.

We determine the four firm-level parameters by matching four key moments: the average markup, the technology adoption rate (the fraction of firms adopting the frontier technology, S_t), the fixed costs-to-sales ratio, and the dividend payout-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 help mainly for identifying the demand elasticity (ξ) and the marginal production costs (f_o); the adoption rate help main for identifying the technology adoption costs (f_a), the fixed costs to sales ratio help mainly for identifying the fixed production costs (f), and the dividend payout ratio matters for identifying both of the marginal production costs (f_o) and the fixed operating cost (f).

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 firmsâ 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 a 71% adoption rate of advanced digital technologies among U.S. firms in 2022—we set the threshold at 45 keyword mentions to approximate

a 70% adoption rate in our sample.[12] 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 (36%), and other technology-linked investments such as intangible capital (24%) and knowledge capital (27%). These relationships suggest that our measure effectively captures the technological adoption engagement of firms. Further methodological details are provided in Appendix Section A.6.

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 5 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 the incentives for adoption.

Recall that the aggregate capital K represents the long-run industry state, which firms consider in strategic competition with other firms. A high level of aggregate capital is associated with lower aggregate prices P, reflecting increased price competition as firms undercut each other. To examine the effects of strategic competition in the model, Figure 6

[12]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 âinnovation activities.â

plots the policy functions and value functions against either firm-level physical capital (k) or technology capital (n), varying the aggregate price level, P. The top-left panel shows that the physical investment rate decreases in firm-level physical capital, reflecting diminishing returns in the revenue function. Additionally, firms reduce their physical investment when the aggregate price falls because heightened competition leads to lower marginal revenue, inducing a strategic substitution effect. Consequently, as shown in the bottom-left panel, firm value decreases when aggregate prices fall, as intensified competition erodes profitability, holding the firm's technology adoption decision constant.

The top-right panel illustrates the technology adoption decision. As shown, 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. Different from physical investment decisions, firms are more likely to adopt the frontier technology when aggregate prices decline due to competition rising. This occurs because adopting the frontier technology reduces marginal production costs, partially offsetting the impact of lower aggregate prices, which creates a strategic complementarity effect. However, this effect does not fully counteract the decline in marginal revenue resulting from lower aggregate prices, so firm value still decreases as aggregate prices fall.

Figure 7 illustrates the model-implied markups as a function of the 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). 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 value premium and the markup 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 $\xi = 5$, operating production costs $f_o = 0.19$, the adoption cost $f_a = 7.8$ and the fixed production cost $f = 6.8$ 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.

The model also aligns reasonably well with the observed asset pricing moments, as reported in Table 6. 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. More 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 low-productivity firms that are more exposed to frontier shocks than growth firms. This happens because value firms lag behind the technology frontier and cannot catch up due to adoption costs, making them riskier. Additionally, 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 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 higher benefits of technology adoption. 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 dividend payout ratio. Importantly, the low marginal production costs 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, aligning closely with the data value of 1.2. Their new income to sales ratio is also low at 0.03, consistent with the data. More importantly, due to the high operating costs 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 (technology adoption benefits) and firm demand elasticities are critical for explaining the decline in the value premium and the rise in markups. Both trends are primarily driven by high-markup firms.

5 Inspecting the mechanism

In this section, we conduct counterfactual analyses to examine the economic forces driving the model's overall fit.

5.1 The role of cross-time heterogeneity of technology efficiency

One of the key heterogeneities in the model is the cross-time increase in the efficiency of the aggregate technology frontier, $\bar{s}$. To assess its impact on changes in the value premium and markups, we increase the incremental efficiency of the aggregate technology frontier in the post-2000 economy by 50% for both groups, while keeping cross-firm heterogeneities unchanged. Table 7 reports the result (the row "More efficiency increase in frontier"). We find that the markup of low-markup firms rises to 1.38, larger the baseline, while the value

premium declines to 0.15%. This result is intuitive: with a greater improvement in frontier technology efficiency compared to the baseline model, the effective technology adoption fraction increases, reducing the realized marginal production costs for low-markup firms. As a result, their average markup rises, and their value premium declines. Meanwhile, the markup for high-markup firms increases to 2.84 —counterfactually high relative to the data —while their value premium remains negligible, similar to the baseline.

5.2 The role of heterogeneity in firm demand elasticity

In the model, firms face a downward-sloping demand curve, with market power determined by the elasticity of the firm demand curve, ξ. To analyze the impact of heterogeneity in demand elasticity, we set the demand elasticity ξ of low-markup firms equal to that of high-markup firms, effectively giving low-markup firms the same level of market power as high-markup firms. The results of this counterfactual scenario are reported in the row labeled "Shutting down heterogeneity in firm demand elasticity" in Table 7. Our findings indicate that the markup and net income to sales ratio of low-markup firms increase from 1.34 and 0.03 in the baseline to 1.60 and 0.09, respectively, while the adoption rate declines to 43% from 62%. Intuitively, granting low-markup firms significantly higher market power results in higher markups. This, in turn, drives an increase in their net income to sales ratio due to the increase in operating profits.

More importantly, the value premium decreases significantly, from 5.34% to -0.16%. This is intuitive: with higher markups among low-markup firms, production costs become less significant for their future cash flows. Consequently, the cross-sectional exposures to the frontier shock shrink substantially between value and growth firms, resulting in a value premium close to zero. Overall, removing heterogeneity in demand elasticity significantly reduces the differences in markups and value premiums between low- and high-markup groups.

5.3 The role of heterogeneity in marginal production costs

Another key aspect of cross-group heterogeneity in the model calibration is the difference in marginal production costs (f_o), which determines the equilibrium benefits of technology adoption. To examine the impact of this heterogeneity on the value premium and markups, we set f_o for the low-markup group equal to that of the high-markup group. (Recall that, in the baseline calibration, the low-markup group has higher marginal opera costs than the high-markup group, resulting in lower adoption benefits.) The results of this counterfactual scenario are presented in the row labeled "Shutting down heterogeneity in marginal production costs f_o" in Table 7. We find that the markup, adoption rate, and net income to sales ratio increase to 2.16, 0.89, and 0.17, respectively —substantially higher than both the baseline calibration and the observed data. Additionally, the value premium for the low-markup group decreases to 0, which is counterfactually too low compared to both the baseline and the data.

This result is intuitive: with marginal production costs for the low-markup group being lower than in the baseline, the average markup increases, and firms are more likely to adopt frontier technology. At the same time, the operating costs channel becomes less quantitatively significant for the future cash flows of low-markup firms. This reduction leads to a diminished exposure to the frontier shock and, consequently, a negligible value premium.

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

To investigate the impact of the heterogeneity in adoption costs on the value premium and markups, we set f_a of the high markup group the same as the low markup group (Recall that in the baseline calibration, high markup group has a higher technology adoption costs than the low markup group). The row "Shutting down heterogeneity in technology adoption costs f_a" in Table 7 reports the result. We find that the technology adoption rate for high-

markup firms increases from 0.83 to 0.90. However, the markup, net income to sales ratio, and value premium remain unchanged compared to the baseline and the data. This outcome occurs because technology adoption costs influence only the decision to adopt technology, without having a significant quantitative impact on firms' pricing, operating costs, or future cash flows.

Additionally, to investigate the impact of the heterogeneity in fixed production costs, we set f of the high markup group the same as the low markup group (Recall that in the baseline calibration, high markup group has a higher fixed production costs than the low markup group). The row "Shutting down heterogeneity in fixed operating costs f" in Table 7 reports the result. We find that the net-income ratio for high-markup firms increases from 0.09 to 0.28. However, the markup, technology adoption rate, and value premium remain largedly unchanged compared to the baseline and the data. This occurs because fixed production costs do not directly affect firms' physical investment or technology adoption decisions; additionally, these costs are relatively small compared to sales, thus they do not have a significant quantitative impact on firms' markups or future cash flows.

5.5 The role of price of risks

To examine the impact of the risk prices of aggregate productivity shocks and aggregate technology frontier shocks, we set γ_x and γ_s to zero separately for both low- and high-markup groups in two counterfactual analyses. The rows labeled "Zero risk price of aggregate productivity shocks" and "Zero risk price of aggregate frontier shocks" in Table7 present the results.

We find that the risk prices of both aggregate shocks significantly influence the value premium, with the risk price of the frontier shock having a much larger impact. However, neither risk price substantially affects the quantity moments of markup, technology adoption rate, fixed costs-to-sales ratio, or dividend payout ratio.

Specifically, setting the risk price of the aggregate frontier shock to zero reduces the value

premium of the low-markup group from 5.3% to zero. In contrast, setting the risk price of the aggregate productivity shock to zero only lowers the value premium of low-markup firms to 4.51%, highlighting that the aggregate technology frontier shock is the primary driver of the value premium. Notably, setting risk prices to zero does not quantitatively affect the value premium of the high-markup group. This is because there is no risk dispersion between value and growth firms within the high-markup group, so changes in risk prices have no material effect.

5.6 The role of strategic interactions

In the model, firms take their competitors' strategies into account because these strategies influence aggregate prices, as captured in the revenue function: $rev_{_{j,t}} = P_t^{1-\frac{\eta}{\xi}} \left(X_t z_{j,t} k_{j,t}\right)^{1-\frac{1}{\xi}}$. Notably, the term $1-\frac{\eta}{\xi}$ directly affects aggregate pricing dynamics in firms' revenues. To examine the impact of strategic interactions on quantities and prices, we focus on industry demand elasticity (η), given the pre-calibrated ξ. A higher industry demand elasticity (η) makes the aggregate price more elastic, thereby diminishing the influence of strategic interactions on firms.[13]

Specifically, we increase η from 4 to 4.05 for the high markup group, which reduces the aggregate price impact in firms' revenues $(1-\frac{\eta}{\xi})$ by half, reflecting a weaker effect of strategic competition. To achieve the same reduction, we increase η from 4 to 6 for the low markup group. The row "Weaker strategic competition" in Table 7 shows that the value premium for the low-markup group declines significantly in the post-2000 economy, dropping from 5.34% to 0.18%. This result is intuitive: as industry prices become less responsive to aggregate shocks, firmsâ exposure to frontier shocks converges, leading to reduced within-industry risk dispersion and, consequently, a lower value premium.

Additionally, the adoption rate and net income-to-sales ratio for low-markup firms increase from 0.62 and 0.03 to 0.90 and 0.14, respectively, indicating that weaker degree of

[13] In the limiting case where industry demand elasticity (η) approaches infinity, the aggregate price is constant and therefore does not influence firms' output or strategies.

strategic interactions encourage firms to adopt technology more readily and generate higher net income. For high-markup firms, the markup, adoption rate, and dividend payout ratio also increase slightly due to the effects of weaker strategic interactions. However, the magnitude of these changes is smaller for the high-markup group, as the degree of strategic interactions within this group is already relatively low.

6 Aggregate implications and testing of the technology adoption channel

In this section, we examine the implications of technology adoption for aggregate productivity changes and perform empirical tests to validate the model's mechanisms related to technology adoption and markups.

6.1 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 Loecker, Eeckhout, and Unger (2020)), 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 demand elasticity—creates inefficiencies in capital allocation, affecting aggregate productivity.

In the model we show that measured aggregate productivity differs significantly between low- and high-markup firms in the post-2000 economy, with the latter group exhibiting significantly higher productivity.[14] This prediction is corroborated by data: high-markup

[14]Measured aggregate productivity is calculated as the firm sales-weighted average of firm-specific produc-

firms consistently outperform their low-markup counterparts in measured productivity. As illustrated in Appendix Figure A.1, this gap has widened over time. The model implies that the divergence stems from two forces: (1) high marginal production costs among low-markup firms affect efficient capital allocation, suppressing their productivity despite low market power; and (2) low marginal costs among high-markup firms facilitate capital efficiency, improving their productivity despite their high market power.

To quantify these mechanisms, Figure 8 compares counterfactual scenarios in our model. When firms across markup groups share identical (low) demand elasticity, aggregate productivity declines by 0.7% relative to the baseline due to exacerbated capital misallocation[15]. Conversely, equalizing marginal production costs (at low levels) boosts aggregate productivity by 1.3%. These results underscore that the interplay of marginal production cost heterogeneity and market power disparities is a critical driver of sluggish TFP growth. 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 growth.

6.2 Empirical test of the technology adoption channel

In this section, we empirically test our model's main channel that the rise of markup and the decline of value premium concentrate among companies that most likely to adopt new technologies. To identify those firms, we conduct textual analysis by counting the appearance of technology-related keywords in a company's annual reports.[16] We consider firms that mention these keywords most frequently in their 10-K filings as most likely to

tivity.

[15] Aggregate productivity is the weighted average of the measured productivity of the low- and high markup firms

[16] 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.

adopt new technologies.

To demonstrate how technology adoption affects markup and value premium, we sort firms into three groups each year based on the size-adjusted number of keyword appearance 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.[17] 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 these terciles as low-adoption, mid-adoption, and high-adoption firms. We measure the average markup and value premium of companies in each tercile portfolio.

Figure 9 plots the average markup of firms in the low and high technology adoption terciles. This figure and Table 8 Panel A clearly show that high-technology-adoption firms have the largest increase in markup, from 1.8 in 1994 to 2.45 in 2021, whereas low-technology-adoption firms experience very little change in their markup during the past twenty-five years. Table 8 Panel B reports the value premium within each technology-adoption tercile in the post-2000 period. It shows that firms in the lowest technology adoption tercile continue to have a sizable value premium, at 0.56% per month with a t-statistic of 1.88, while the value premium of firms in the highest technology adoption tercile is close to zero and statistically insignificant. Overall, these results confirm the model's main channel that technology adoption plays a significant role in explaining both the rise of the markup and the decline of the value premium in the cross-section of firms.

7 Conclusion

We provide a unified explanation for two major secular trends in recent decades: the decline of the value premium and the rise of markups. We show that these trends are closely connected. Empirically, we find that the decline in the value premium is primarily driven by

[17] 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.

firms with high markups, whereas it remains substantial among low-markup firms. Furthermore, the same high-markup firms that contribute to the decline of the value premium also drive the rise in aggregate markups. To explain these patterns, we develop a dynamic model incorporating technological frontier shocks, costly technology adoption, and strategic interactions. Our model quantitatively replicates these empirical trends, highlighting the crucial role of rising efficiency at the technological frontier and heterogeneous demand elasticity and technology adoption benefits in jointly accounting for the decline in the value premium, the rise in markups, and their cross-sectional variation.

This paper has broad implications for macroeconomics, finance, and industrial organization. Our findings suggest that technological changes play a crucial role in shaping asset prices and markups. Additionally, we show that risk premiums are key determinants of firms' technology adoption decisions, which, in turn, influence their markups. Furthermore, our results indicate that the economic forces driving recent shifts in industrial structure —such as the rise in aggregate markups —are closely linked to changes in the risk premium. These trends should be examined jointly within a unified framework to gain a more comprehensive understanding of their interplay.

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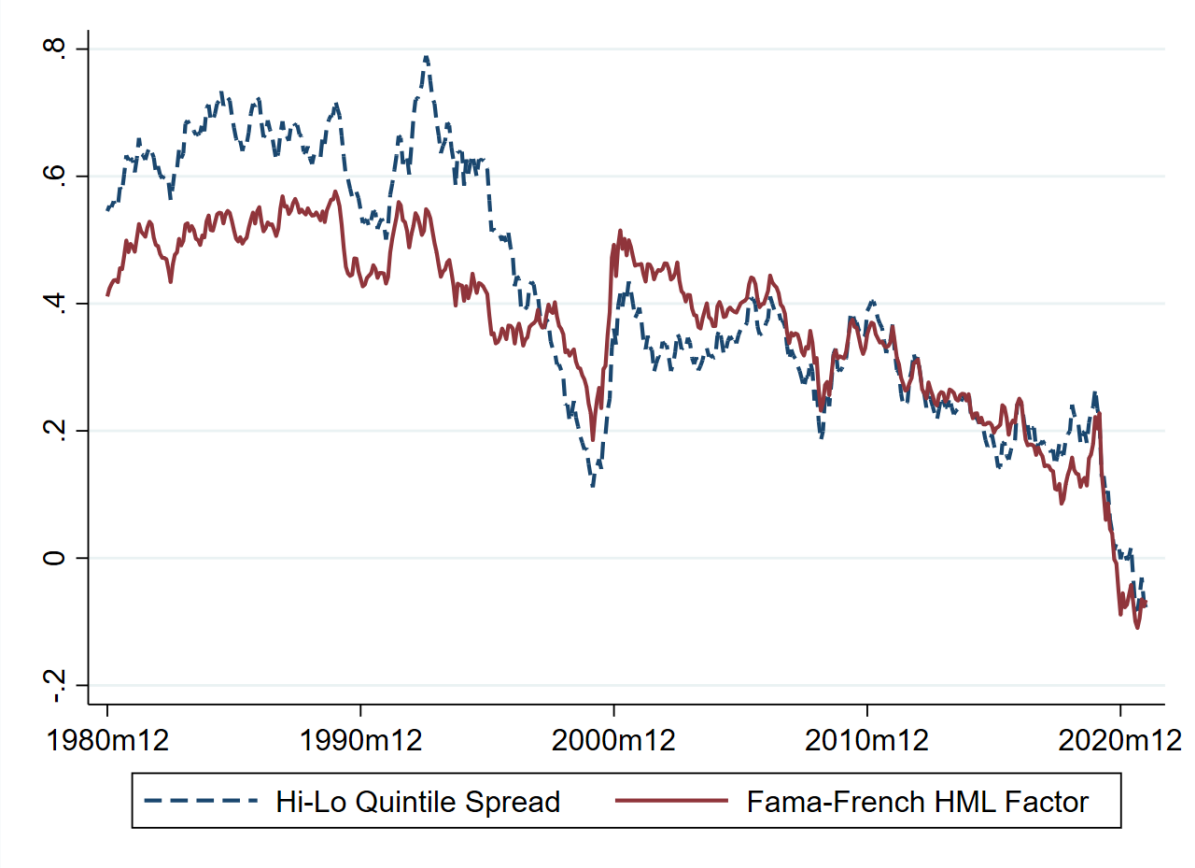
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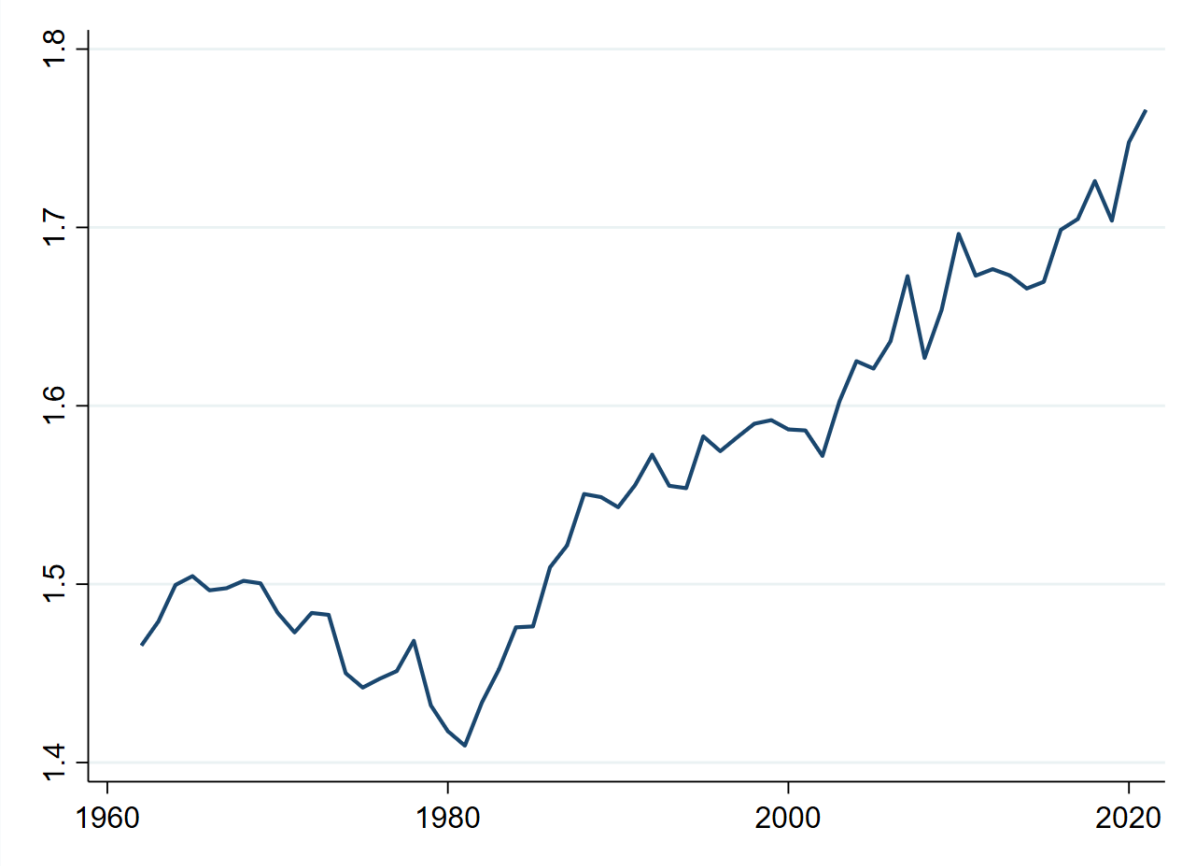
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Figure 1: Value premium over time



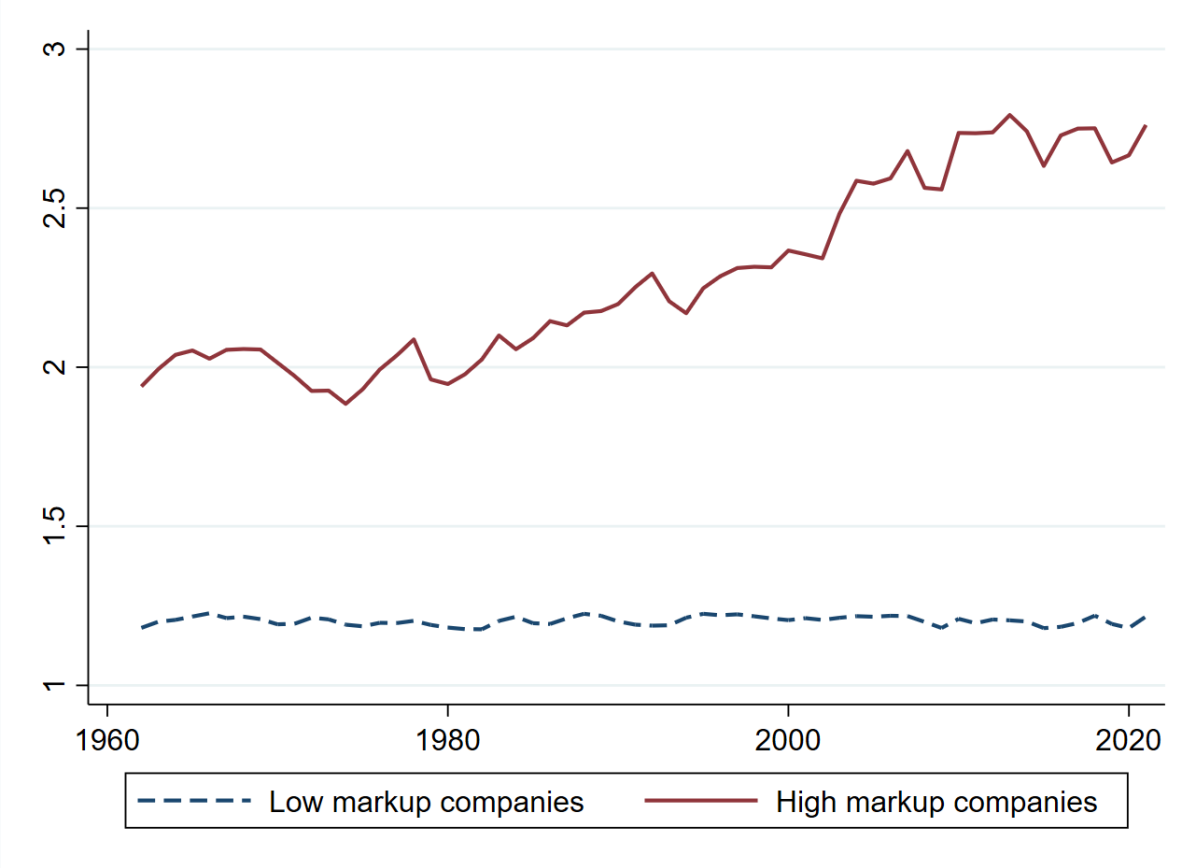
Notes: This figure plots 20-year rolling-average returns of the top book-to-market quintile (value stocks) minus bottom book-to market-quintile (growth stocks) and the Fama-French HML factor.

Figure 2: Aggregate markups over time



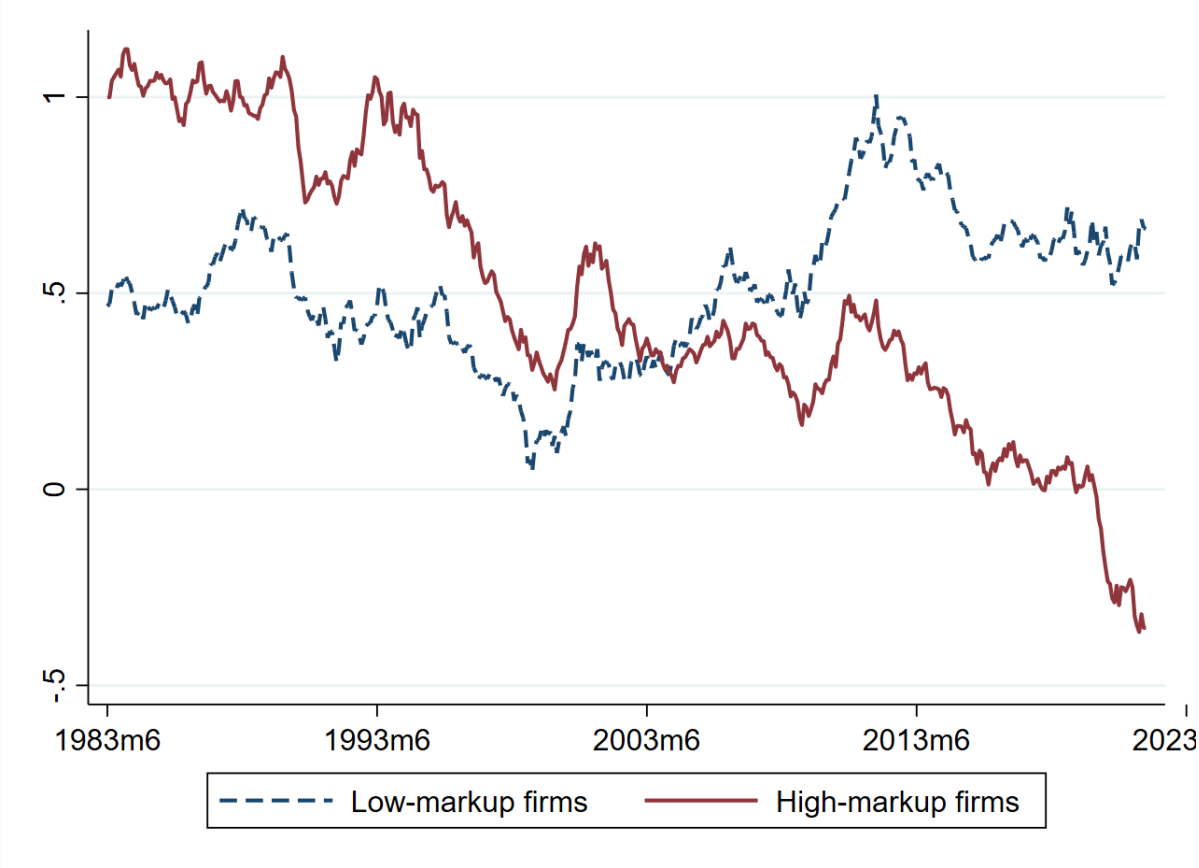
Notes: This figure plots the aggregate (revenue-weighted average) markups of US public firms, excluding utilities and financial companies. We measure a firm's markup as the ratio between its revenue to its cost of goods sold.

Figure 3: Markups of high- and low-markup firms



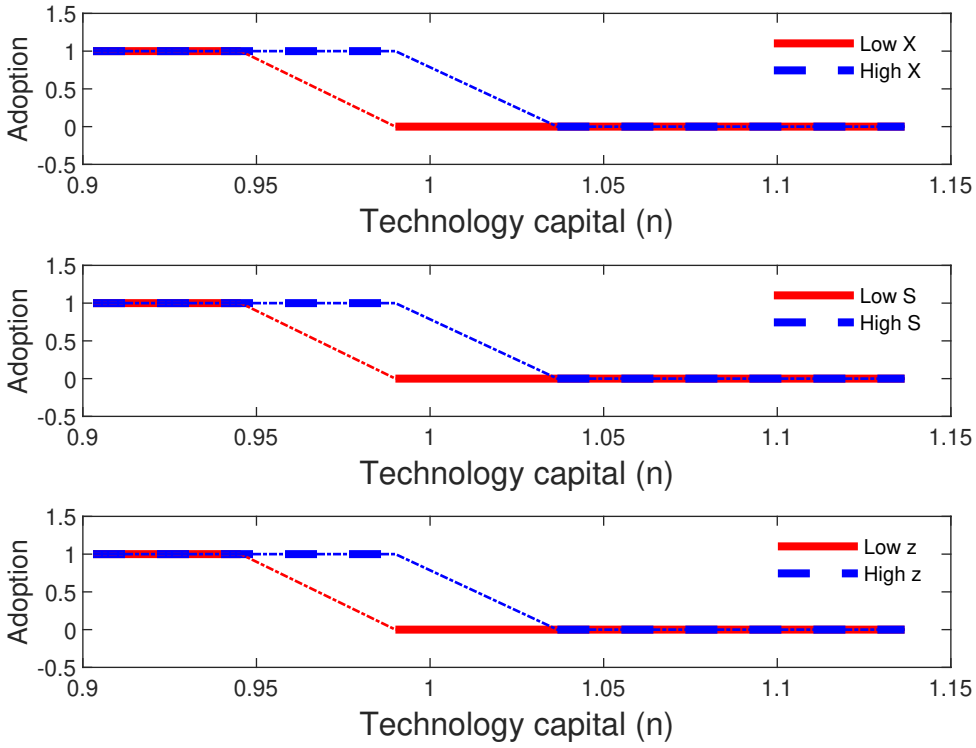
Notes: This figure plots the revenue-weighted average markup of low and high-markup firms. Low-markup firms are defined as those in the bottom NYSE tercile by markup, while high-markup firms are those in the top NYSE tercile. A firm's markup is calculated as the ratio of its sales to its cost of goods sold.

Figure 4: Value premium of high- and low-markup firms



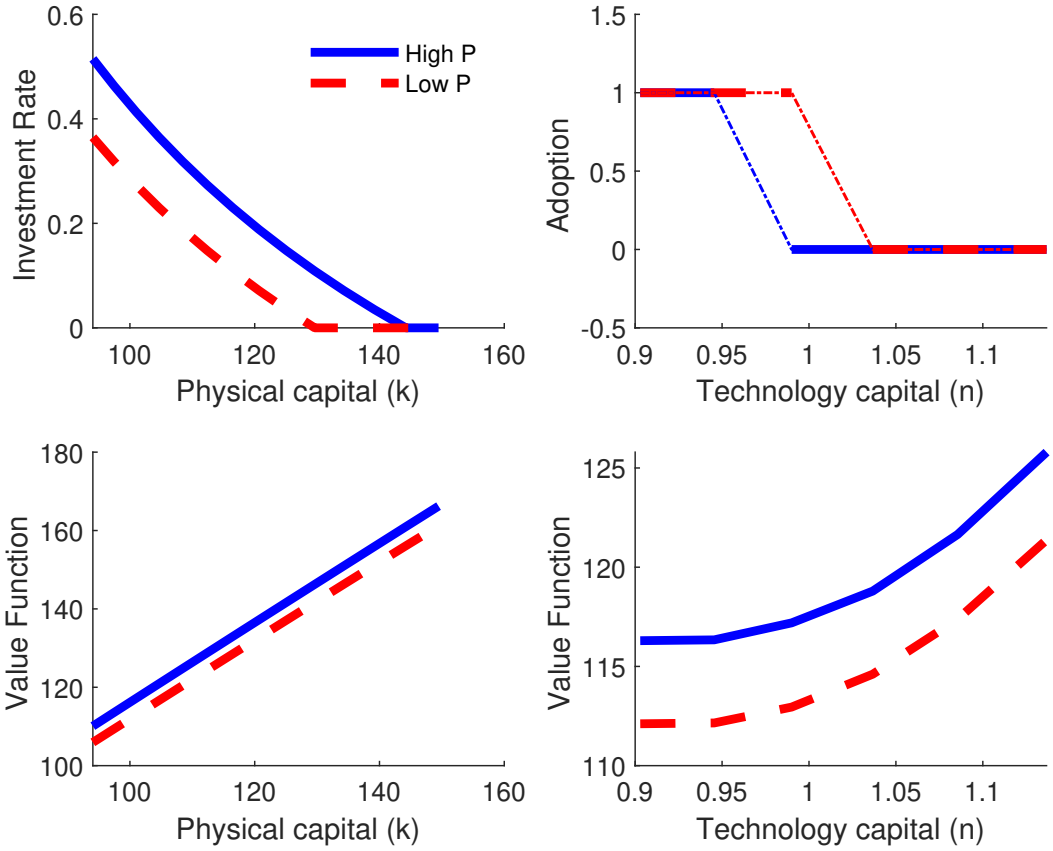
Notes: This figure shows the 20-year rolling average value premium for high- and low-markup firms. Firms are independently double-sorted into terciles based on their markup and quintiles based on their book-to-market ratio. The value premium in the top and bottom markup terciles is calculated as the value-weighted return of top book-to-market firms minus the value-weighted return of bottom book-to-market firms within each tercile.

Figure 5: Technology adoption policies



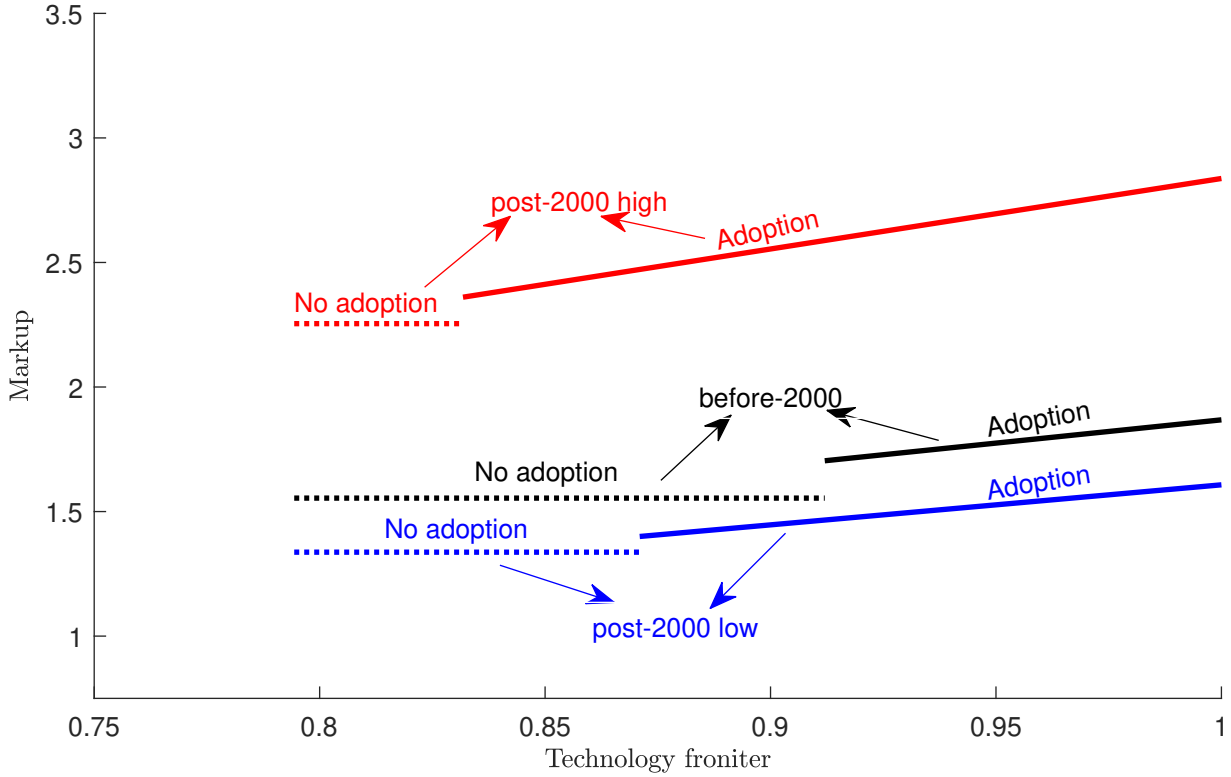
Notes: This figure plots the technology adoption decisions as a function of the technology capital (n) under the pre-2000 economy calibration. The three panels depict adoption policies with different levels of aggregate productivity X (top), technology frontier productivity S (middle), and firm-level 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 5.

Figure 6: Policy functions and value functions



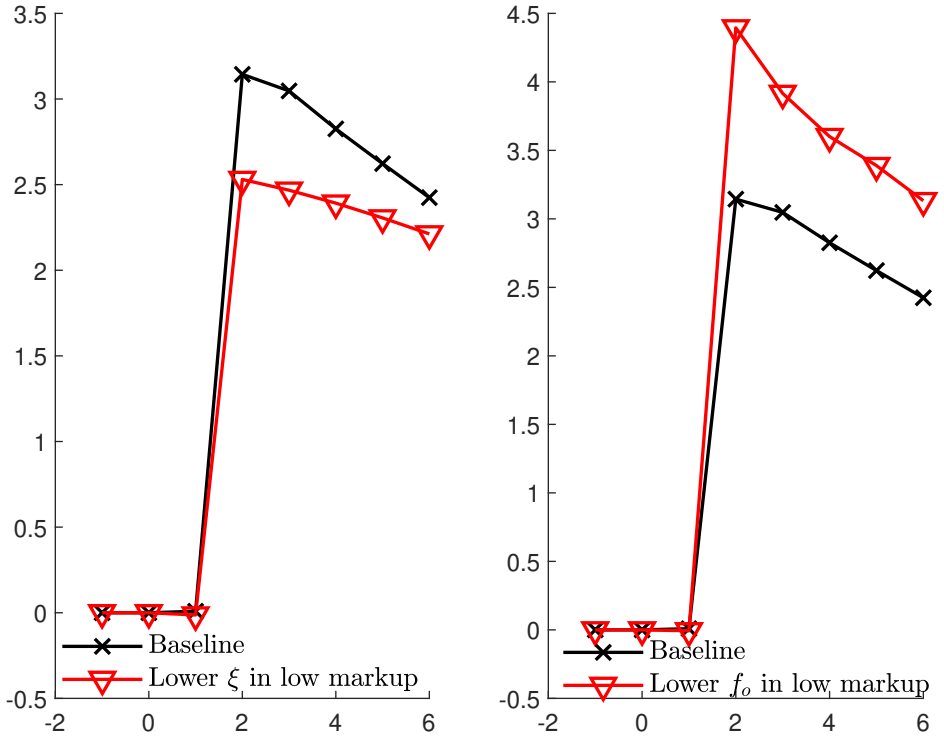
Notes: This figure plots the policy functions and value functions as functions of either physical capital (k) or technology capital (n), with different values of aggregate price P under the pre-2000 economy calibration, while other state variables are fixed at the long-run mean of the corresponding economies. The parameter values used in the calibration are provided in Table 5.

Figure 7: Model implied markups



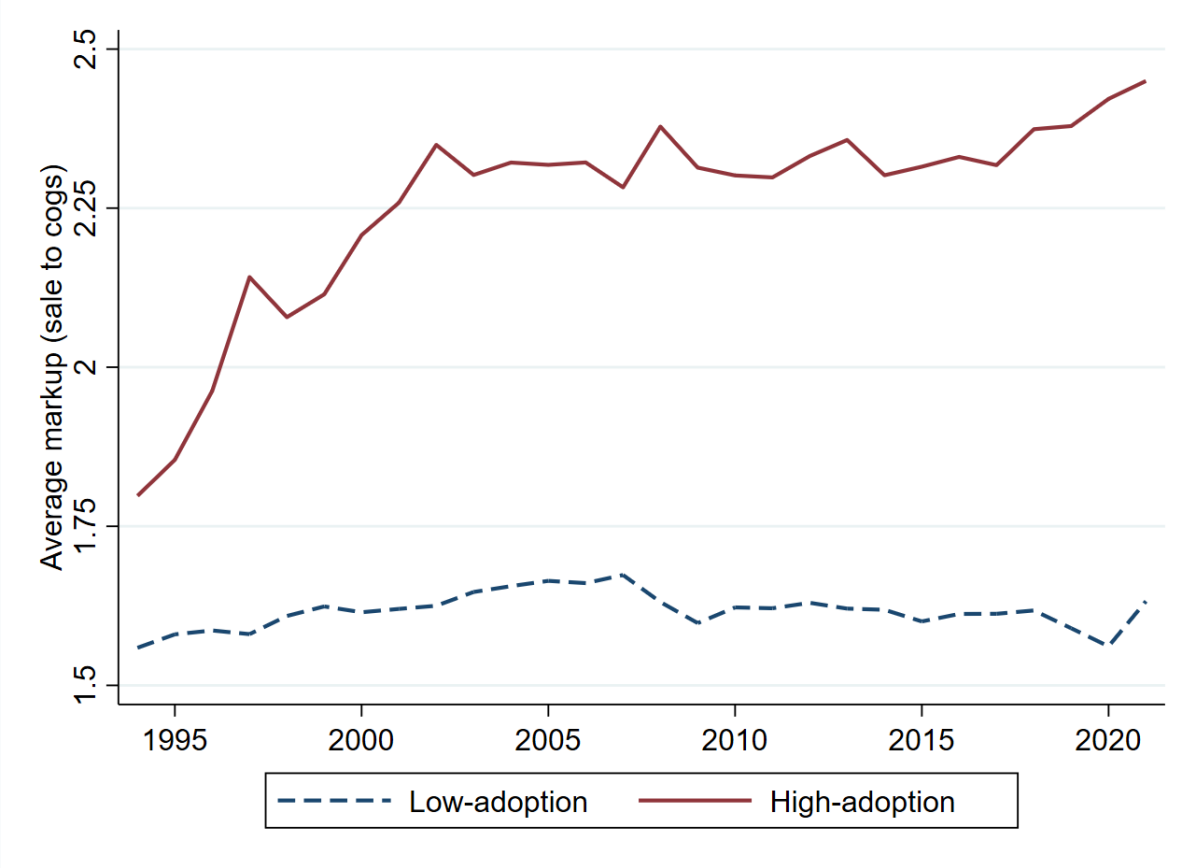
Notes: This figure plots model implied markups as a function of the scaled technology frontier, $\frac{S_t}{\max S_t}$, under various calibrations. The blue lines correspond to the pre-2000 economy, while the red and black lines represent the low-markup and high-markup groups in the post-2000 economy, 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 5.

Figure 8: 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 the 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.

Figure 9: Markups and technology adoption



Notes: This figure plots the average markup of low and high technology adoption firms. Technology adoption is measured using a size-adjusted count of technology-related keywords in firms' annual reports. Companies are first grouped by market capitalization, and within each size group, they are sorted into terciles based on the number of technology-related keywords. Firms in the lowest tercile are labeled as low-adoption firms, while those in the highest tercile are classified as high-adoption firms

Table 1: Decline in the value premium

Panel A: pre-2000 period

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Quintile spread		Decile spread		HML factor	
Mkt-Rf		-0.15***		-0.12*		-0.27***
		(-2.63)		(-1.69)		(-6.38)
Constant	0.48**	0.55***	0.58**	0.64***	0.45***	0.58***
	(2.55)	(2.93)	(2.47)	(2.66)	(2.81)	(3.93)
Observations	456	456	456	456	456	456
Adjusted R^2	0.000	0.033	0.000	0.012	0.000	0.166

Panel B: post-2000 period

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Quintile spread		Decile spread		HML factor	
Mkt-Rf		0.33***		0.50***		0.12*
		(4.24)		(5.11)		(1.77)
Constant	-0.06	-0.31	-0.07	-0.44	-0.05	-0.13
	(-0.21)	(-1.10)	(-0.19)	(-1.20)	(-0.22)	(-0.58)
Observations	246	246	246	246	246	246
Adjusted R^2	0.000	0.127	0.000	0.163	0.000	0.028

Notes: This table reports the average monthly returns (columns 1, 3, and 5) and CAPM alphas (columns 2, 4, and 6) of the value premium across two distinct sample periods. We present the return difference between the top and bottom book-to-market quintiles (columns 1 and 2), the top and bottom book-to-market deciles (columns 3 and 4), as well as the Fama-French HML factor (columns 5 and 6). Panel A shows results for the pre-2000 sample period (July 1963 to June 2001), while Panel B reports results for the post-2000 sample period (July 2001 to December 2021). T-statistics (in parentheses) are computed using Newey-West standard errors with three lags. Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Table 2: Increase in markups

Panel A: aggregate markup

VARIABLES	(1) Equal weighted	(2) Asset weighted	(3) Revenue weighted
Post-2000	0.26***	0.33***	0.16***
	(8.28)	(8.42)	(6.46)
Constant	1.61***	1.60***	1.50***
	(54.15)	(105.75)	(93.50)
Observations	60	60	60
Adjusted R^2	0.706	0.829	0.691

Panel B: markups in different groups

VARIABLES	(1) Low markup tercile	(2) Mid markup tercile	(3) High markup tercile
Post-2000	0.00	0.10***	0.54***
	(0.04)	(7.37)	(8.76)
Constant	1.20***	1.41***	2.10***
	(371.43)	(158.78)	(53.96)
Observations	60	60	60
Adjusted R^2	-0.017	0.712	0.800

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

Table 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*
	(1.12)	(1.74)	(2.55)	(2.67)	(2.95)	(1.80)
Mid markup	0.34	0.46*	0.63***	0.82***	1.14***	0.80***
	(1.23)	(1.87)	(2.89)	(3.54)	(4.37)	(3.86)
High markup	0.50**	0.61***	0.56***	0.79***	1.28***	0.77***
	(2.05)	(2.74)	(2.59)	(3.28)	(4.28)	(3.25)
High-Low	0.16	0.15	-0.02	0.17	0.51***	0.35
	(0.98)	(1.04)	(-0.15)	(0.97)	(3.01)	(1.48)

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*
	(1.39)	(2.70)	(2.19)	(1.76)	(2.31)	(1.91)
Mid markup	1.10***	0.88***	0.87**	0.89**	0.85*	-0.25
	(2.95)	(2.70)	(2.46)	(2.28)	(1.68)	(-0.65)
High markup	0.85***	0.78**	0.67**	0.56	0.55	-0.30
	(3.09)	(2.56)	(2.03)	(1.41)	(1.19)	(-0.88)
High-Low	0.35*	0.03	-0.10	-0.14	-0.58*	-0.92***
	(1.78)	(0.13)	(-0.55)	(-0.65)	(-1.79)	(-2.74)

Notes: This table presents the average monthly returns of portfolios double-sorted by book-to-market ratios and markup levels across different sample periods. Markup is calculated as sales divided by the cost of goods sold. 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 with three lags.Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Table 4: Markups and change in value premium

	(1)	(2)	(3)	(4)	(5)	(6)
	Value premium: quintile spread			Value premium: CAPM alpha		
VARIABLES	Low-markup	High-markup	High - Low	Low-markup	High-markup	High - Low
Post-2000	0.20	-1.07***	-1.27***	-0.18	-1.37***	-1.11**
	(0.50)	(-2.59)	(-3.09)	(-0.46)	(-3.06)	(-2.55)
Mkt-Rf				-0.22***	-0.20***	0.24***
				(-3.39)	(-3.04)	(4.33)
Post2000×Mkt				0.58***	0.49***	-0.29**
				(5.65)	(4.12)	(-2.48)
Constant	0.42*	0.77***	0.35	0.53**	0.90***	0.23
	(1.80)	(3.25)	(1.48)	(2.37)	(4.48)	(1.02)
Observations	702	702	702	702	702	702
Adjusted R^2	0.000	0.012	0.015	0.072	0.057	0.047

Notes: This table reports the change in the value premium among low-markup firms (columns 1 and 4) and high-markup firms (columns 2 and 5), as well as the difference in value premium between low- and high-markup firms (columns 3 and 6). Firms are sorted into terciles based on their markup, calculated as sales divided by the cost of goods sold, and into quintiles based on their book-to-market ratio, using NYSE cutoff points. The value premium is defined as the difference in value-weighted returns between the top and bottom book-to-market quintiles within each markup tercile. The change in value premium is estimated using a Post-2000 dummy variable, which indicates whether a month occurs after June 2001. All t-statistics (in parentheses) are calculated using Newey-West standard errors with three lags. Superscripts ***, **, * indiate statistical significance at the 1%, 5%, and 10%, respectively.

Table 5: 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 6: 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	0.44	0.44
Fixed cost to sales	0.15	0.17
Net income to sales	0.05	0.05

Notes: This table presents the selected moments implied by the baseline model calibration in the pre-2000 economy. We compare the moments in the data ("Data") with moments of simulated data ("Model"). In the data, value premium is the difference in return between the top bm quintile and the bottom bm quintile. Markup is defined as the ratio between revenue and cost of goods sold. We classify that a firm adopts technology if its annual report mentions technology related keywords by more than 45 times. Details on the classification of technology adoption are in the appendix. Fixed cost is proxied by the SG&A expense minus R&D and advertising expense. We use net income before extraordinary items in the data to measure net income to sales ratio. We winsorize accounting based variables at the top and bottom 2.5%. The model-implied moments are the mean value of the corresponding moments 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 7: Selected data versus model-implied moments: post-2000 economy

Low markup group					High markup group				
Markup	Adoption	F/S	Dividend	V.P.	Markup	Adoption	F/S	Dividend	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 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 strategic competition ($\uparrow$ industry demand elasticity η)									
1.36	0.90	0.01	0.14	0.18	2.66	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. Specification 0 reports the data, while specification 1 presents the baseline calibration. Specification 2 increases the aggregate technology frontier efficiency ($\bar{s}$) by 50% compared to the baseline calibration. Specification 3 sets the 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 8: Technology adoption, markup and value premium

Panel A: average markup of firms sorted by technology adoption

	(1)	(2)	(3)
Year	Low tech adoption	Mid tech adoption	High tech adoption
1994	1.56	1.58	1.80
2021	1.63	1.96	2.45
Change in markup	0.07	0.38	0.65

Panel B: value premium of firms sorted by technology adoption

	(1)	(2)	(3)
VARIABLES	Low tech adoption	Mid tech adoption	High tech adoption
Constant	0.56*	0.30	0.02
	(1.88)	(0.88)	(0.07)
Observations	246	246	246
Adjusted R^2	0.000	0.000	0.000

Notes: This table presents the average markup and value premium of firms across three technology-adoption terciles. To construct these terciles, 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, labeled as low-, mid-, and high-adoption firms. Panel A reports the average markup for each tercile in 1994 and 2021. Panel B reports the value premium within each tercile for the period from July 2001 to December 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 each technology-adoption tercile, separately for small-cap and large-cap companies. 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 with three lags Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Appendix For Online Publication

A Data Appendix

This section describes additional robustness checks in the data.

A.1 Alternative sample periods cutoffs

We first examine the decline of the value premium in alternative sample periods. Table A.1 presents the results. 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.

Novy-Marx (2011) and Campbell, Giglio, and Polk (2023) find that value premium is stronger when measured within industries. We show in Table A.2 that the intra-industry value premium has also declined. Columns 1 and 2 show that the intra-industry value premium is indeed stronger than the traditional value premium in the pre-2000 period, but columns 3 and 4 show that in the post-2000 period, the intra-industry value premium is no longer significant and is close to zero, similar to the traditional value premium.

Table A.3 reports the CAPM alpha of markup and book-to-market sorted portfolios. Panel A shows the CAPM alpha in the pre-2000 period. As expected, in all three markup terciles, the value premium generates significantly positive CAPM alpha and the difference in the CAPM alpha between low and high markup companies is not significant in the pre-2000 period. Panel B shows the CAPM alpha in the post-2000 period. Although the CAPM alphas are not significant in the post-2000 period, their ranking is similar to our main result. The CAPM alpha of the value premium among low markup firms is the highest, at 0.36% per month or 4.32% per year, whereas the CAPM alphas in the mid- and high-markup tercile are negative. The difference in the CAPM alpha between the low and high-markup terciles is significant.

A.2 Alternative measures of markup

In our main specification, we measure markup as the ratio between a company's revenue and its cost of goods sold. In this section, we use alternative methods to measure markups and show our results remain qualitatively the same. We consider an alternative definition of the markup. In this definition, we include Selling, General, and Administrative (SG&A) expenses into the marginal cost. The SG&A expense item from COMPUSTAT includes some items that are not typically considered as marginal costs, such as R&D expenses and

marketing expenses. Hence, we remove those expenses from the marginal cost. Table A.5 Panel A shows the average returns of portfolios sorted by book-to-market ratio and the alternative markup in the post-2000 period. The results are similar to our baseline findings. In the low-markup tercile, the value premium is significantly positive, whereas in the high-markup tercile, the value premium is insignificant.

Additionally, our alternative method is to measure markup at the industry level. Specifically, we measure the industry revenue and cost of goods sold as the total revenue 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. Table A.4 Panels A and B show the average return of BM and industry markup sorted portfolios in the pre- and post-2000 period. Similar to our main results, in the pre-2000 periods, the value premium is significant in all three industry-markup terciles. In the post-2000 period, the value premium is only significantly among firms in low-markup industries. Panel C estimates the change in value premium between the two periods and finds that the change is insignificant in low-markup industries and is significantly negative in high-markup industries.

A.3 Excluding micro-cap stocks

We check whether our results are robust to excluding micro-cap stocks. We identify micro-cap stocks as those with a market cap smaller than the 10th NYSE size percentile. We remove these firms from our sample. Table A.5 Panel B reports the average returns of portfolios sorted by book-to-market ratio and the alternative markup in the post-2000 period when micro-cap stocks are removed. The results are not affected. In the low-markup tercile, the value premium is 0.6% per month and statistically significant. In mid- and high-markup terciles, the value premium is insignificant. The difference in the value premium between the high- and low-markup terciles is significantly negative.

A.4 Excluding superstar firms

Autor, Dorn, Katz, Patterson, and Van Reenen (2020) proposes that the rise of superstar firms is an important explanation of the decline of the labor's share of GDP 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 driving our results. We find this not to be the case. Our main findings remain qualitatively the same if we remove superstar firms from our sample. We first identify superstar firms as those in each industry's top market capitalization decile. These firms account for the majority of the market value of the US stock market. We remove these firms from our sample. Table A.6 Panels A and B show the average returns of BM and markup sorted portfolios in the pre- and post-2000 period. In the pre-2000 period, the value premium is strong in all three markup terciles, whereas in the post-2000 period, the value premium is only significant in the low-markup tercile, consistent with our main findings. Pane C columns 1 to 3 show the average markup of non-superstar firms also increased significantly in the post-2000 periods. Panel C columns 4 to 6 show that the increase in markup is mainly driven by firms in the mid-, and low-markup terciles.

A.5 Relationships with other characteristics

In this section, we test whether alternative stories can explain the decline of the value premium. First, we report the cross-sectional correlation between markup and various other stock characteristics in Table A.7. We find that in the cross-section, markup has little correlation with other stock characteristics. For example, the correlation of markup with size is only 9%, with book-to-markup is -14%, and with profitability is 12%. We also compare the correlation between markup and other proxies of intangible assets. The correlation between markup and R&D expenditure is 14%. We obtain data on a firm's intangible capital from the Peters and Taylor (2017) dataset and find that the correlation between markup and intangibles is small, at around 10%. This exercise suggests that markup is a unique feature of the firm and is unlike a proxy of other firm characteristics.

Next, we test whether these other firm characteristics can help us understand the decline of the value premium. To do so, we sort companies into terciles based on their size, R&D expense, profitability, and various types of intangible assets. We then measure the value premium in these portfolios in the pre-2000 and post-2000 periods. Table A.8 shows the results. In the pre-2000 period, the value premium is significantly positive in almost all the characteristic-sorted portfolios (the only exception is among large-cap stocks). However, in the post-2000 period, none of these portfolios produces significant value premium. Therefore, this exercise shows that these characteristics do not explain why the value premium has declined.

A.6 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 publically traded US firms from Loughran-McDonald website.[18] 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.

In a company's 10-K filing, we count how many times it mentions technology-related words. The root keywords we use are: technology, system, software, and data. We also include any derivatives of these words, such as technologies and technological. After this exercise, we obtain the annual count of these keywords from each company in our sample from 1994 to 2021. Next, we make the assumption that if a firm's 10-K filling mentions technology keywords by more than 45 times in a given year, then the firm has adopted a new technology. We chose the number 45 such that the average technology adoption rate of all companies in our sample in the post-2000 period is 71%, which matches with the European Investment Bank Investment Survey 2022 that reports 73% of firms in the United States adopted advanced digital technologies, e.g. advanced robotics, 3D printing, big data analytics, and artificial intelligence.

Based on this threshold, we compute the technology adoption rate in the pre-2000 period to be 42% (i.e., 42% of firms mentioned technology-related keywords more than 45 times in

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

their 10-K filings in the pre-2000 period). We also compute the technology adoption rate of low- and high-markup companies in the post-2000 period. In the post-2000 period, on average, 61% of firms in the low-markup tercile adopt new technologies, while this fraction for high-markup firms is 82%.

B Numerical Algorithm

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

B.1 Solving the monopolistic competitive equilibrium

The Bellman equation for the firm problem is as the following:

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

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 (X,S,K). 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

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

Now we describe our solution algorithm details. We first initialize the forecast rules $\hat{\Gamma}_P^{(1)}$ and $\hat{\Gamma}_K^{(1)}$ with guessed initial coefficients $\alpha_P^{(1)}\left(X,S\right)$ and $\beta_P^{(1)}\left(X,S\right)$, and $\alpha_K^{(1)}\left(X,S\right)$ and $\beta_K^{(1)}\left(X,S\right)$. Then the follow 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 $\hat{\Gamma}_P^{(q)}$ and $\hat{\Gamma}_K^{(q)}$. 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 predeterrmined 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 grids points. The grid for technology capital is constructed log-linearly. We discretize the aggregate and firm-specific productivities with into 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 $n_t = \log(N_t)$, we let $n_{nN} = \bar{s}(\mathcal{T}) + 3\sigma_s$. To make sure the technology capital is on the grids, for any $m \in [1, nN-1]$, we set $n_m = n_{nN} + (nN - m)\log(1-\delta_N)$ where we choose the number of grids nN such that $n_1 < \bar{s}(\mathcal{T}) - 3\sigma_s$. After that, for any $j \in [1, n_s]$, we let $s_j = n_{m'(j)}$ 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 $\mathrm{i} = 1, \ldots, \mathrm{n}_k\mathrm{n}_n\mathrm{n}_z$ 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. 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 R2 implied by the following forecasting regressions for price $\hat{p}_t$ and aggregate capital $\hat{K}_{t+1}$ are close to 1:

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

B.2 Solving the Bellman equation

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

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

$$s.t.\ d_t = rev_t - i_t - h_t - oc_t - ac_t - f, \tag{22}$$

$$\text{where } oc_t = \begin{cases} \frac{f_o}{S_t} y_t & \text{if } \phi_t = 1 \\ \frac{f_o}{(1-\delta_n) n_{t-1}} y_t & \text{if } \phi_t = 0 \end{cases}, \tag{23}$$

$$ac_t = \begin{cases} f_a & \text{if } \phi_t = 1 \\ 0 & \text{if } \phi_t = 0 \end{cases}, \tag{24}$$

$$n_t = \begin{cases} S_t, & \text{if } \phi_t = 1 \\ (1-\delta_n) n_{t-1}, & \text{if } \phi_t = 0 \end{cases}, \tag{25}$$

$$h_t = \begin{cases} \left(S_t - (1-\delta_n) n_{t-1}\right) \cdot 1_{\{S_t - (1-\delta_n) n_{t-1} > 0\}}, & \text{if } \phi_t = 1 \\ 0, & \text{if } \phi_t = 0 \end{cases}. \tag{26}$$

$$\begin{aligned} k_{t+1} &= (1-\delta_k)\, k_t + i_t \\ x_{t+1} &= \rho_x x_t + \sigma_x \varepsilon^x_{t+1} \\ z_{t+1} &= \bar{z}\,(1-\rho_z) + \rho_z z_t + \sigma_z \varepsilon^z_{t+1} \\ s_{t+1} &= (1-\rho_s)\, \bar{s}\,(\mathcal{T}) + \rho_s s_t + \sigma_s \varepsilon^s_{t+1}, \end{aligned}$$

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

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:

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

$$s.t.\ d_t = rev_t - i_t - h_t - oc_t - ac_t - f, \tag{27}$$

$$\text{where } oc_t = \frac{f_o}{(1-\delta_n)\, n_{t-1}} y_t, \tag{28}$$

$$ac_t = 0, \tag{29}$$

$$n_t = (1-\delta_n) n_{t-1}, \tag{30}$$

$$\begin{aligned} k_{t+1} &= (1-\delta_k)\, k_t + i_t \\ x_{t+1} &= \rho_x x_t + \sigma_x \varepsilon^x_{t+1} \\ z_{t+1} &= \bar{z}\,(1-\rho_z) + \rho_z z_t + \sigma_z \varepsilon^z_{t+1} \\ s_{t+1} &= (1-\rho_s)\, \bar{s}\,(\mathcal{T}) + \rho_s s_t + \sigma_s \varepsilon^s_{t+1}, \end{aligned}$$

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 (30). Therefore, numerically we solve the Bellman equation through

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

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

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

$$s.t.\ d_t = rev_t - i_t - h_t - oc_t - ac_t - f, \tag{31}$$

$$\text{where } oc_t = \frac{f_o}{S_t}y_t, \tag{32}$$

$$ac_t = f_a, \tag{33}$$

$$n_t = S_t, \tag{34}$$

$$h_t = \left(S_t - (1-\delta_n)n_{t-1}\right)\cdot 1_{\{S_t-(1-\delta_n)n_{t-1}>0\}}. \tag{35}$$

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

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

$$z_{t+1} = \bar{z}\,(1-\rho_z) + \rho_z z_t + \sigma_z \varepsilon_{t+1}^z$$

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

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

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

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.

C Markup decomposition

The dynamic problem in our model setup is given by

$$v_{j,t}\left(\Theta_t\right) = \max_{i_{j,t},\phi_{j,t}} : \left\{d_{j,t} + E_t\left[M_{t,t+1}v_{j,t+1}\left(\Theta_{t+1}\right)\right]\right\}. \tag{36}$$

$$\text{s.t.} \qquad k_{j,t+1} = i_{j,t} + (1-\delta_k)k_{j,t}, \tag{37}$$

$$d_{j,t} = P_t^{1-\frac{\eta}{\xi}}\left(X_t z_{j,t} k_{j,t}\right)^{1-\frac{1}{\xi}} - i_{j,t} - h_{j,t} - oc_{j,t}\left(y_{j,t}\right) - ac_{j,t} - f. \tag{38}$$

where $\Theta_t = \left(k_{j,t}, n_{t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$.

In addition, since $y_{j,t} = X_t z_{j,t} k_{j,t}$, we know $\frac{\partial y_{j,t}}{\partial k_{j,t}} = X_t z_{j,t}$. Let $oc_{j,t} = \varkappa_{j,t}\left(y_{j,t}, \phi_{j,t}\right)$.

Evaluating at the optimum, the first order condition with respect to $k_{j,t}$ is given by the

following expression:

$$P_t^{1-\frac{\eta}{\xi}}\left(1-\frac{1}{\xi}\right)y_{j,t}^{-\frac{1}{\xi}}\frac{\partial y_{j,t}}{\partial k_{j,t}}-\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial y_{j,t}}\frac{\partial y_{j,t}}{\partial k_{j,t}}-\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial \phi_{j,t}}\frac{\partial \phi_{j,t}}{\partial y_{j,t}}\frac{\partial y_{j,t}}{\partial k_{j,t}}+E_t\left[M_{t+1}\frac{\partial v_{j,t+1}\left(\Theta_{t+1}\right)}{\partial k_{j,t}}\right]=0$$

$$\Longrightarrow\left[\frac{P_t^{\xi-\eta}}{y_{j,t}}\right]^{\frac{1}{\xi}}=\left(\frac{\xi}{\xi-1}\right)\left\{\frac{\partial \varkappa_t\left(y_{j,t},\phi_{j,t}\right)}{\partial y_t}+\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial \phi_{j,t}}\frac{\partial \phi_{j,t}}{\partial y_{j,t}}-\frac{1}{X_t z_{j,t}}E_t\left[M_{t+1}\frac{\partial v_{j,t+1}\left(\Theta_{t+1}\right)}{\partial k_{j,t}}\right]\right\}$$

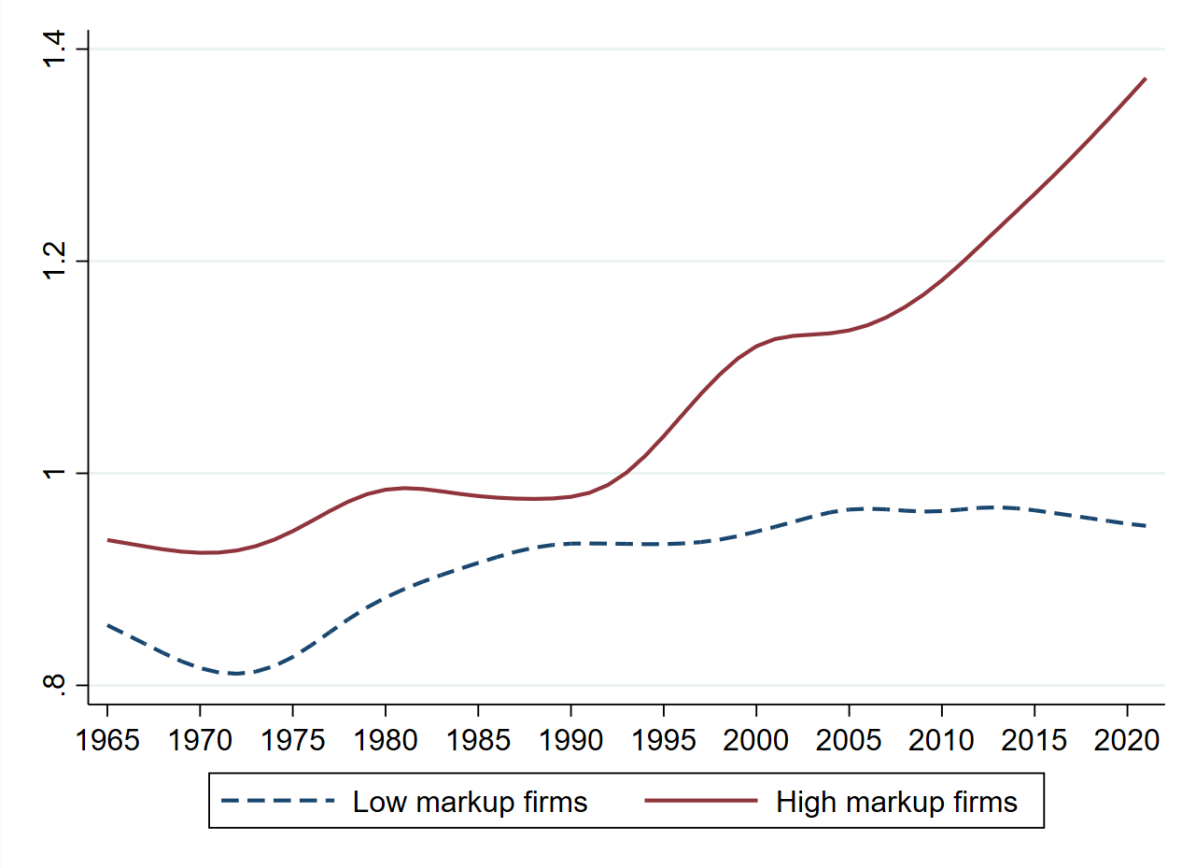
Since $\mu_{j,t}=\frac{p_{j,t}}{\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial y_{j,t}}}=\frac{\left[\frac{P_t^{\xi-\eta}}{y_{j,t}}\right]^{\frac{1}{\xi}}}{\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial y_{j,t}}}$, we know

$$\mu_{j,t}=\left(\frac{\xi}{\xi-1}\right)\left[1+\frac{\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial \phi_{j,t}}\frac{\partial \phi_{j,t}}{\partial y_{j,t}}-\frac{1}{X_t z_{j,t}}E_t\left[M_{t+1}\frac{\partial v_{j,t+1}(\Theta_{t+1})}{\partial k_{j,t}}\right]}{\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial y_{j,t}}}\right]$$

$$=\left(\frac{\xi}{\xi-1}\right)\left[1+\frac{\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial \phi_{j,t}}\frac{\partial \phi_{j,t}}{\partial k_{j,t}}-E_t\left[M_{t+1}\frac{\partial v_{j,t+1}(\Theta_{t+1})}{\partial k_{j,t}}\right]}{\frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial k_{j,t}}}\right].$$

In our model, the endogenous adoption choice and future firm value affects firm's capital choice, which makes the markup change over time and across firms.

Figure A.1: Measured productivity of low-markup and high-markup firms



Notes: This figure plots the measured aggregate productivity (firm size weighted firm-specfic productivity) of firms in the low-markup tercile and high-markup tercile from 1965 to 2021. The firm-specific productivity is from İmrohoroğlu and Tüzel (2014). The aggregate productivity is smoothed using an HP filter with an annual smoothing parameter of 100.

Table A.1: Value premium in alternative sample periods

This table reports the average monthly return and the CAPM alpha 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), as the difference in returns between the top and bottom book-to-market deciles (in columns 3 and 4), and as the Fama-French HML factor (in columns 5 and 6). 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 with 3 lags. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: post-1993 period value premium

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Quintile spread		Decile spread		HML factor	
Mkt-Rf		0.13		0.25**		-0.06
		(1.48)		(2.25)		(-0.74)
Constant	0.01	-0.09	0.05	-0.14	0.08	0.12
	(0.06)	(-0.31)	(0.16)	(-0.41)	(0.38)	(0.51)
Observations	342	342	342	342	342	342
Adjusted R^2	0.000	0.018	0.000	0.044	0.000	0.003

Panel B: post-financial-crisis value premium

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Quintile spread		Decile spread		HML factor	
Mkt-Rf		0.40***		0.53***		0.12
		(3.33)		(3.45)		(1.29)
Constant	-0.40	-0.89**	-0.58	-1.23**	-0.25	-0.39
	(-0.94)	(-2.05)	(-1.07)	(-2.16)	(-0.84)	(-1.12)
Observations	132	132	132	132	132	132
Adjusted R^2	0.000	0.135	0.000	0.147	0.000	0.018

Panel C: post-2000 and exclude Covid-19 period

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Quintile spread		Decile spread		HML factor	
Mkt-Rf		0.31***		0.49***		0.10
		(4.52)		(5.48)		(1.49)
Constant	0.01	-0.18	0.03	-0.27	0.01	-0.05
	(0.02)	(-0.78)	(0.10)	(-0.81)	(0.05)	(-0.26)
Observations	222	222	222	222	222	222
Adjusted R^2	0.000	0.127	0.000	0.177	0.000	0.022

Table A.2: Decline of intra-industry value premium

This table reports the performance intra-industry value premium. Specifically, we measure value premium (the difference in return between stocks in the top and bottom book-to-market quintile) within in each Fama-French 30 industry and average across industries to compute the intra-industry value premium. We use the total industry market cap as weights to average each industry's value premium. Columns 1 and 2 report the average value premium and the CAPM alpha of value premium from 1963m7 to 2001m6. Columns 3 and 4 report the average value premium and the CAPM alpha of value premium from 2001m7 to 2021m12. All t-statistics (in parentheses) are based on Newey-West standard errors with 3 lags. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Pre-2000		Post-2000	
Mkt-Rf		-3.18		27.03***
		(-0.58)		(4.37)
Constant	0.73***	0.75***	0.08	-0.13
	(4.46)	(4.50)	(0.27)	(-0.49)
Observations	456	456	246	246
Adjusted R^2	0.000	-0.000	0.000	0.103

Table A.3: CAPM alpha of BM and markup sorted portfolios

This table reports the average monthly CAPM alpha of bm and markup double-sorted portfolios in different sample periods. We sort firms based on their markup, measured as sales divided by the cost of goods sold, into terciles. We also sort firms based on their book-to-market ratio into quntiles. We use NYSE cut-off points. Panel A reports the return in the pre-2000 periods, which is from 1963m7 to 2001m6. Panel B reports the return in the post-2000 periods, which is from 2001m7 to 2021m12. We omit beta, the adjusted R-squared, and the number of observations to save space. All t-statistics (in parentheses) are based on Newey-West standard errors with 3 lags. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

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	-0.27*	-0.06	0.10	0.11	0.26	0.53**
	(-1.95)	(-0.44)	(0.79)	(0.97)	(1.63)	(2.37)
Mid markup	-0.26***	-0.09	0.14	0.37**	0.64***	0.90***
	(-2.60)	(-0.85)	(1.27)	(2.58)	(3.84)	(4.48)
High markup	-0.02	0.11	0.10	0.32**	0.75***	0.77***
	(-0.19)	(1.23)	(0.87)	(2.13)	(3.97)	(3.16)
High-Low	0.25	0.17	0.00	0.21	0.49***	0.23
	(1.63)	(1.14)	(0.02)	(1.18)	(2.88)	(1.02)

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	-0.28	0.15	-0.05	-0.19	0.08	0.36
	(-1.62)	(0.93)	(-0.35)	(-0.97)	(0.31)	(1.11)
Mid markup	0.28	0.11	0.00	0.02	-0.19	-0.47
	(1.59)	(0.88)	(0.02)	(0.16)	(-0.62)	(-1.16)
High markup	0.18	0.06	-0.11	-0.29	-0.35	-0.52
	(1.58)	(0.50)	(-0.74)	(-1.46)	(-1.18)	(-1.63)
High-Low	0.45**	-0.09	-0.06	-0.09	-0.43	-0.88**
	(2.20)	(-0.44)	(-0.30)	(-0.39)	(-1.21)	(-2.36)

Table A.4: Average return of BM and industry markup sorted portfolios

This table reports the average return of bm and industry markup double-sorted portfolios in different sample periods. We sort SIC 2-digit industries into terciles based on each industry's markup, which is measured as the industry total revenue divided by industry total cost of goods sold. We also sort firms based on their book-to-market ratio into quntiles independently. Panel A reports the return in the pre-2000 periods, which is from 1963m7 to 2001m6. Panel B reports the return in the post-2000 periods, which is from 2001m7 to 2021m12. Panel C reports the change in value premium between the two periods. All t-statistics (in parentheses) are based on Newey-West standard errors with 3 lags. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

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

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup industries	0.18	0.31	0.53**	0.62***	0.75***	0.57**
	(0.60)	(1.22)	(2.34)	(2.69)	(2.86)	(2.49)
Mid markup industries	0.35	0.58**	0.55**	0.70***	0.94***	0.60***
	(1.37)	(2.40)	(2.32)	(2.89)	(3.43)	(2.95)
High markup industries	0.51**	0.58**	0.69***	0.79***	1.20***	0.69***
	(2.01)	(2.50)	(3.14)	(3.32)	(4.44)	(3.20)
High-Low	0.33*	0.27	0.16	0.17	0.45***	0.12
	(1.70)	(1.62)	(0.98)	(0.92)	(2.75)	(0.49)

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

	(1) Low BM	(2) 2	(3) 3	(4) 4	(5) High BM	(6) High-Low
Low markup industries	0.67**	0.87***	0.71**	0.64	1.25**	0.58*
	(2.01)	(2.98)	(2.07)	(1.58)	(2.59)	(1.76)
Mid markup industries	0.80***	0.88***	0.95***	0.94***	0.88	0.08
	(3.03)	(3.08)	(2.77)	(2.60)	(1.64)	(0.19)
High markup industries	0.91***	0.76**	0.70**	0.64	0.61	-0.30
	(2.92)	(2.46)	(2.08)	(1.63)	(1.40)	(-1.01)
High-Low	0.24	-0.11	-0.01	0.00	-0.64*	-0.88**
	(1.02)	(-0.53)	(-0.03)	(0.01)	(-1.94)	(-2.54)

Panel C: change in value premium in industry markup sorted portfolios

VARIABLES	(1) Low	(2) Mid	(3) High	(4) Low	(5) Mid	(6) High
Post-2000	0.01	-0.52	-0.99***	-0.34	-1.03**	-1.13***
	(0.03)	(-1.10)	(-2.69)	(-0.85)	(-2.29)	(-3.14)
Mkt-Rf				-0.20***	-0.07	0.01
				(-3.36)	(-1.18)	(0.09)
Post dummy×Mkt-Rf				0.54***	0.71***	0.18*
				(5.42)	(5.21)	(1.76)
Constant	0.57**	0.60***	0.69***	0.67***	0.63***	0.68***
	(2.49)	(2.94)	(3.20)	(2.99)	(3.06)	(3.11)
Observations	702	702	702	702	702	702
Adjusted R^2	-0.001	0.001	0.011	0.056	0.118	0.021

Table A.5: Alternative definition of markup and exclude micro-cap stocks

This table reports post-2000 period average return of bm and markup sorted portfolios. In Panel A, 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

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

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. In Panel B, we exlcude micro-cap stocks, which are stocks in the bottom NYSE size decile. All t-statistics (in parentheses) are based on Newey-West standard errors with 3 lags. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: post-2000 value premium (alternative markup definition)

	(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**
	(1.55)	(2.72)	(1.89)	(2.12)	(2.34)	(1.97)
Mid markup	0.92**	0.71**	0.81**	0.78**	1.03**	0.12
	(2.36)	(2.33)	(2.28)	(1.99)	(2.03)	(0.34)
High markup	0.89***	0.87***	0.69**	0.50	0.43	-0.47
	(3.14)	(2.79)	(2.20)	(1.22)	(0.91)	(-1.35)
High-Low	0.33*	0.09	-0.05	-0.35	-0.76**	-1.09***
	(1.77)	(0.45)	(-0.26)	(-1.49)	(-2.16)	(-3.13)

Panel B: post-2000 value premium (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*
	(1.43)	(2.71)	(2.20)	(1.75)	(2.29)	(1.83)
Mid markup	1.10***	0.88***	0.88**	0.88**	0.83	-0.27
	(2.96)	(2.70)	(2.48)	(2.26)	(1.65)	(-0.68)
High markup	0.85***	0.78**	0.66**	0.54	0.50	-0.35
	(3.10)	(2.56)	(2.01)	(1.38)	(1.07)	(-1.02)
High-Low	0.34*	0.02	-0.11	-0.15	-0.61*	-0.95***
	(1.72)	(0.12)	(-0.58)	(-0.68)	(-1.86)	(-2.74)

Table A.6: Exclude superstar firms

This table reports the average return and markups in different sample periods. We exclude superstar firms from the calculation of returns and markups. Superstar firms are defined as firms in the top market capitalization decile of each industry. Panel A reports the return in the pre-2000 periods, which is from 1963m7 to 2001m6. Panel B reports the return in the post-2000 periods, which is from 2001m7 to 2021m12. Panel C reports the average markup of non-superstar firms in columns 1, 2, and 3 with equal-weighted average, asset-weighted average, and revenue-weighted average, respectively. Panel C columns 4, 5, and 6 report the revenue-weighted markups of firms in the low-, mid-, and high-markup terciles. All t-statistics (in parentheses) are based on Newey-West standard errors with 3 lags. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

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	0.28	0.74**	0.70***	0.86***	0.94***	0.66***
	(0.78)	(2.57)	(2.67)	(3.34)	(3.43)	(2.63)
Mid markup	0.03	0.61**	0.62**	0.90***	1.07***	1.04***
	(0.07)	(2.27)	(2.42)	(3.56)	(3.73)	(4.44)
High markup	0.53*	0.79***	0.86***	1.01***	1.22***	0.69***
	(1.84)	(3.26)	(3.53)	(3.90)	(4.04)	(2.97)
High-Low	0.24	0.05	0.16	0.14	0.28*	0.03
	(1.45)	(0.38)	(1.35)	(0.99)	(1.71)	(0.13)

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	0.46	0.64	1.09***	0.94**	1.04**	0.58*
	(0.98)	(1.60)	(2.64)	(2.13)	(2.06)	(1.77)
Mid markup	0.76*	0.94**	1.05***	0.87**	0.86*	0.10
	(1.89)	(2.51)	(2.77)	(2.05)	(1.69)	(0.34)
High markup	1.03***	0.95***	0.82**	0.70	0.81	-0.22
	(2.99)	(2.72)	(2.17)	(1.54)	(1.63)	(-0.63)
High-Low	0.57***	0.31*	-0.27	-0.25	-0.23	-0.79**
	(2.69)	(1.89)	(-1.48)	(-1.35)	(-1.04)	(-2.40)

Panel C: change in aggregate markup and markup in each group

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate markup			Markup by group		
VARIABLES	EW	AW	RW	Low	Mid	High
Post-2000	0.23***	0.21***	0.10***	-0.00	0.11***	0.46***
	(7.96)	(10.03)	(6.42)	(-0.90)	(7.70)	(7.84)
Constant	1.60***	1.54***	1.44***	1.19***	1.41***	1.98***
	(57.67)	(96.30)	(99.73)	(473.31)	(149.21)	(46.03)
Observations	60	60	60	60	60	60
Adjusted R^2	0.689	0.775	0.579	0.009	0.748	0.742

Table A.7: Cross-sectional correlation between markup and stock characteristics

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 revenue 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 extra-ordinary items divided by asset. 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.

	mu	size	bm	roa	r&d	intan	know.	org.
Markup	1.00							
Size	0.09	1.00						
BM	-0.14	-0.36	1.00					
ROA	0.12	0.35	-0.05	1.00				
R&D	0.14	-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

Table A.8: Value premium in alternative characteristic sorted portfolios

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 3 report pre-2000 period result, which is from 1963m7 to 2001m6, and columns 4 to 6 report post-2000 period, which is from 2001m7 to 2021m12. Size is the log of market cap. BM is book-to-market ratio. ROA is net income before extra-ordinary items divided by asset. 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 with 3 lags. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Pre-2000			Post-2000	
Panel A: sort by size						
	Small	Mid	Large	Small	Mid	Large
Value premium	0.62***	0.41*	0.35	0.43	-0.11	-0.27
	(2.70)	(1.67)	(1.64)	(1.32)	(-0.36)	(-0.87)
Panel B: sort by R&D						
	Low	Mid	High	Low	Mid	High
Value premium	0.59**	0.57**	0.94***	0.13	0.16	0.16
	(2.50)	(2.18)	(3.14)	(0.35)	(0.51)	(0.45)
Panel C: sort by ROA						
	Low	Mid	High	Low	Mid	High
Value premium	1.00***	0.58***	0.62**	-0.20	-0.46	0.32
	(3.40)	(2.67)	(2.38)	(-0.53)	(-1.18)	(0.97)
Panel D: sort by intangible capital						
	Low	Mid	High	Low	Mid	High
Value premium	0.81***	0.53**	0.57**	-0.15	0.08	0.07
	(3.57)	(2.45)	(2.40)	(-0.37)	(0.24)	(0.19)
Panel E: sort by knowledge capital						
	Low	Mid	High	Low	Mid	High
Value premium	0.66***	0.50**	0.63***	-0.07	0.39	-0.01
	(3.27)	(2.35)	(2.62)	(-0.21)	(1.16)	(-0.03)
Panel F: sort by organizational capital						
	Low	Mid	High	Low	Mid	High
Value premium	0.65***	0.58**	0.55**	-0.17	0.15	0.28
	(2.97)	(2.39)	(2.27)	(-0.48)	(0.48)	(0.62)