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

Xiaoji Lin† Chao Ying‡ Terry Zhang§

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**Abstract**

We provide a unified explanation for two major macro-financial trends: the declining value premium and rising markups. Using firm-level data, we show that both patterns are driven by high-markup firms, while low-markup firms exhibit stable value premia and markups. We develop a dynamic model of monopolistic competition featuring endogenous technology adoption and strategic interactions. The model shows that these trends result from (i) rising efficiency of the technology frontier and (ii) heterogeneity in adoption incentives and demand elasticity. These heterogeneities distort capital allocation and help explain the recent slowdown in aggregate productivity growth.

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

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†University of Minnesota, xlin6@umn.edu.

‡Chinese University of Hong Kong, chaoying@cuhk.edu.hk.

§Australian National University, terry.zhang@anu.edu.au.

# 1 Introduction

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

Empirically, we document a novel fact: the decline in the value premium and the rise in markups are predominantly driven by high-markup firms. In contrast, low-markup firms have seen no change in either their value premium or markup levels. Moreover, high-markup firms experience significantly faster productivity growth than their low-markup counterparts. We develop a dynamic monopolistic competition model featuring endogenous technology adoption 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 decline in the value premium, the rise in markups, and their difference across firms. Furthermore, the model implies that the high marginal production costs among low-markup firms and the high market power among high-markup firms hinder capital allocation, contributing to the slowdown in aggregate productivity growth.

We begin by documenting a substantial decline in value premium over recent decades, consistent with findings in the literature. Specifically, the annualized return spread between value and growth stocks decreased sharply, falling from 5.8% during the pre-2000 period to -0.7% in the post-2000 period. Over the same period, corporate markups exhibit a significant rise. In particular, the average markup of publicly traded U.S. firms rises from 1.5 in 1962-2000 to 1.7 in 2001-2021. Crucially, we show that the decline of the value premium and the rise of markups are primarily concentrated among high-markup firms. For this group, the value premium falls sharply from 9.2% to -3.6%, while markups increase from 2.1 to 2.6 over the same period. In contrast, low-markup firms' value premium stays stable, fluctuating between 5% and 7.4%, while their markups remain unchanged at around 1.2. Moreover,

the average productivity of the high-markup firms is significantly higher than that of the low-markup group, with the gap widening significantly in the post-2000 period driven by faster productivity growth among the high-markup group.

To investigate the economic mechanisms linking rising markups to the decline in the value premium, we develop a dynamic monopolistic competition model with three key features: (i) stochastic shifts in the aggregate technology frontier, capturing advances in cutting-edge technologies; (ii) endogenous technology adoption, where firms pay fixed costs to upgrade; and (iii) strategic interactions, as firms take competitors' actions and market structure into account. In the model, firms adopt new technologies to reduce marginal production costs, reflecting the non-rival and scalable nature of technologies including artificial intelligence, Information and Communication Technology (ICT), cloud computing, and automation. These technologies allow firms to expand across product lines or markets, lowering marginal costs (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023; De Ridder, 2024; Hsieh and Rossi-Hansberg, 2023). Furthermore, adoption incentives depend on firms' expectations about competitors' strategies and market conditions, shaping equilibrium outcomes in product market competition.

We first calibrate the model to replicate the pre-2000 economy by focusing on aggregate markups and financial market moments. The results align with empirical findings: the model generates an aggregate markup of 1.5—closely matching historical data—and produces a sizable value premium of 5.1% consistent with observed magnitudes. In the model, markups are jointly determined by firms' demand elasticity and their technology adoption decisions, which influence marginal production costs. Value firms are low-productivity firms that lag behind the technology frontier and are unable to catch up due to the costs of adoption. 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-sectional risk dispersion in the model is driven primarily by exposures to aggregate technology frontier shocks, whereas the market return is driven by both aggregate technology and productivity shocks. Therefore, the CAPM does not capture the cross-sectional variations in book-to-market portfolios.

To study the post-2000 economy, we focus on heterogeneity over time and across high- and low-markup firms. First, we assume a significant increase in the long-run efficiency

of the technology frontier relative to the pre-2000 economy. This captures broad-based advancements in technologies (e.g., AI, automation, ICT) that have reduced production costs across firms since the late 1990s. Second, we introduce heterogeneities between low- and high-markup firms in three key dimensions: (i) demand elasticity, reflecting market power; (ii) marginal production costs (governing the benefits of technology adoption) and the costs of technology adoption—these first two heterogeneities may stem from differences in product innovation that enhance market power or from incompatibilities between new technologies and existing human capital or management practices; and (iii) fixed operating costs. Third, we incorporate within-group heterogeneity in firm-specific productivity, generating dispersion in firm-level risk exposure.

To examine heterogeneity across markup groups, we calibrate the model to match key firm-level moments—average markup, adoption rate, fixed-cost-to-sales, and net-income-to-sales ratios. The calibration shows that high-markup firms have lower marginal production costs and firm demand elasticity. In the model, lower marginal production costs are associated with higher adoption benefit, hence these firms face stronger incentives to adopt, resulting in higher adoption rates. Their lower demand elasticity reflects greater market power, contributing to higher markups. Turning to the value premium, because most of the high-markup firms are near or on the technology frontier in equilibrium, the impact of the frontier technology shocks is similar across firms in the group. As a result, value and growth firms have similar exposure to technology frontier shocks, leading to a near-zero value premium. In contrast to high-markup firms, low-markup firms face higher marginal production costs and greater firms' demand elasticity, resulting in lower adoption rates and smaller markups. Within this group, higher marginal production costs combined with greater demand elasticity widen risk dispersion between value firms and growth firms. Value firms, being low productivity firms in equilibrium face greater exposure to frontier shocks than growth firms, as the high production costs and low adoption incentives make them more exposed to technological frontier shocks, resulting in a sizable value premium. Furthermore, to validate the model's mechanism, we apply textual analysis to financial statements to identify firms with high technology-adoption propensity. We find that these firms exhibit rising markups and virtually zero value premia, consistent with the model's predictions.

We conduct counterfactual analyses to examine the model mechanisms. First, increasing the efficiency of the post-2000 technology frontier by 50% compared to the baseline cal-

ibration eliminates the value premium for low-markup firms and leads to excessively high markups for both firm groups. Second, we isolate the role of cross-group heterogeneity by removing one difference at a time. Differences in marginal production costs and firms' demand elasticity are key drivers of value premium and markup variations. Eliminating both sharply reduces the gap in value premium and markups between groups, with low-markup firms showing a lower value premium and higher markups. In contrast, equalizing the adoption or fixed costs of high-markup firms to those of low-markup firms affects their adoption rates and profitability but has little impact on their value premium or markups, as these costs are relatively small compared to sales for high-markup firms. Lastly, while the risk prices of productivity and frontier shocks both affect the value premium—especially the latter—they do not significantly alter markups. Taken together, these findings demonstrate that increases in the efficiency of the aggregate technology frontier and heterogeneity in marginal production costs and firms' demand elasticity are key in quantitatively explaining both the decline of the value premium and the rise of the markup, which are predominantly driven by high markup firms.

The model also highlights a unique channel that contributes to the slowdown in productivity growth observed over the past several decades (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023; De Ridder, 2024). In our framework, high marginal production costs in low-markup firms and strong market power in high-markup firms jointly amplify capital misallocation.[1] In an impulse response analysis, imposing uniform (low) marginal production costs causes a positive technology frontier shock to raise aggregate productivity by 1.5% relative to the baseline, while uniform (high) market power reduces aggregate productivity by 0.7%.[2] These findings suggest that marginal production cost and market power heterogeneity are key forces behind slow aggregate productivity growth since early 2000s. They also have 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.

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

[2] Aggregate productivity is measured as the average of group productivities.

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). In our model, firms' technology adoption and investment decisions optimally respond to the competitive environment. A key feature of our framework is that firms' collective actions endogenously determine aggregate prices and the industry state, which we summarize by aggregate capital when solving the model. Higher aggregate capital leads to lower aggregate prices, reflecting increased price pressure as competitors expand production and undercut prices. The strength of this strategic effect is governed by the aggregate price elasticity, which plays a key quantitative role in shaping model results. When strategic interactions weaken (i.e., when the industry demand elasticity is higher), the value premium for low-markup firms declines substantially. This is because industry prices become less sensitive to aggregate shocks, reducing firms' differential exposure to frontier shocks. As a result, within-industry risk dispersion shrinks, lowering the value premium. At the same time, low-markup firms experience a notable increase in both their technology adoption rate and net income-to-sales ratio, while these variables change only modestly for high-markup firms.

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

premium, we leverage information from markup dynamics to identify heterogeneity in asset pricing through the marginal production cost and demand elasticity channels.

Our paper contributes to the growing literature on how changes in market structure influence industry dynamics and asset prices. Bustamante (2015), and Corhay, Kung, and Schmid (2020) examine the relationship between product market concentration and risk premia, while Dou, Ji, and Wu (2021, 2022) analyze how strategic competition shapes firms' profitability and risk across industries using dynamic game frameworks. Corhay, Li, and Tong (2022) study the asset pricing implications of shocks to aggregate markups. Our paper differs from these studies in two key respects. Empirically, whereas the existing literature typically emphasizes cross-sectional relationships between market concentration and asset prices, we focus on the trends in markups and the value premium. We show that both are driven by high-markup firms and are closely linked to the broader slowdown in productivity growth. Theoretically, in contrast to prior work that often centers on cross-industry variations, we develop a monopolistic competition model that incorporates (i) strategic interactions within firm groups and (ii) heterogeneity in market power and technology adoption across groups. By endogenizing markup and value premium dynamics through these channels, our framework provides a unified explanation for the evolution of markups, asset prices, and productivity across firms with differing markups.

Our paper also contributes to the literature on asset pricing in production economies.[3] Zhang (2005) examines the value premium within a $q$-theory model, Gomes and Schmid (2010) analyze the relation between financial leverage and stock returns while Belo, Lin, and Bazdresch (2014) and Favilukis and Lin (2016) focus on labor market frictions and asset prices. Moreover, Papanikolaou (2011) and Kogan and Papanikolaou (2014) study the asset pricing implications of investment-specific shocks. Recently, Kogan, Li, and Zhang (2023) develop equilibrium models in which the value and gross profitability premia coexist by emphasizing the role of variable costs. Our paper differs from earlier work in several respects. First, we focus on the economic mechanisms driving the long-run trends in the value premium, aggregate markup, and productivity—an angle largely underexplored in existing literature. Second, we model endogenous technology adoption as a distinct investment

[3]Early contributions include Cochrane (1991, 1996), Jermann (1998), Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), and Carlson, Fisher, and Giammarino (2004), among others. Kogan and Papanikolaou (2012) provide a comprehensive review of developments in this literature.

decision that governs a firm's proximity to the technology frontier, which introduces a new source of risk. Unlike standard models where risk is primarily driven by adjustment costs frictions, our framework generates risk premia from firms' differential exposure to shocks to the technology frontier. Third, building on Parente and Prescott (1994), Greenwood and Yorukoglu (1997), Aghion, Bergeaud, Boppart, Klenow, and Li (2023), and De Ridder (2024), our model incorporates a technology frontier that captures the latest scalable technologies. Firms improve their production efficiency after adopting these frontier technologies. Unlike investment-specific technology shocks, our frontier shock does not affect the price of investment goods.

Lastly, our model integrates with recent industrial organization (IO) literature on industry structure dynamics and strategic competition. Building on foundational work by Maskin and Tirole (1988a,b) and Ericson and Pakes (1995), which introduced Markov Perfect Equilibrium (MPE) to analyze industry dynamics, our paper extends this framework to asset pricing. We are among the first to explore the asset pricing implications of an MPE model that incorporates endogenous technology adoption and firm heterogeneity in market power. To address the substantial computational challenges of MPE with many firms, we employ macroeconomic methods similar to Krusell and Smith (1998). This involves firms basing decisions on their beliefs about industry structure evolution rather than the specific states of competitors. While related computational methods exist, e.g., Weintraub, Benkard, and Van Roy (2008), our approach is distinct: we explicitly model the feedback loop where the aggregate industry state (e.g., aggregate capital) is endogenously shaped by firms' collective behavior. In contrast, Weintraub, Benkard, and Van Roy (2008) assume firms disregard their collective influence on the aggregate state, relying on a fixed law of motion.[4] Our method approximates the industry state and iteratively learns and updates its perceived law of motion. This enables us to capture how strategic price competition influences firms' investment and technology adoption, thereby generating the joint dynamics of markups and risk premia that are central to our paper.

The paper proceeds as follows. Section 2 shows the empirical links between the trends

[4]Weintraub, Benkard, and Van Roy (2010) extend the original oblivious equilibrium (OE) concept—developed in Weintraub, Benkard, and Van Roy (2008) for models with only idiosyncratic shocks—by incorporating aggregate shocks, referring to the resulting framework as the "extended oblivious equilibrium." In the extended OE, firms form expectations about the evolution of a few key aggregate shocks, but it does not allow for price competition that is central to our model.

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

# 2 Empirical findings

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

We collect data from several sources. Accounting information is from Compustat. Data on stock returns and market capitalization are from CRSP. We obtain factor returns and book-to-market (BM) sorted portfolio returns from Ken French's website.[5] We download the cleaned text data of 10-K filings from Loughran-McDonald website for textual analysis in Section 6.1.[6]

## 2.1 The rise of markups

An important macroeconomic trend as documented in the literature is the rapid increase in the aggregate markup. Largely consistent with De Loecker, Eeckhout, and Unger (2020) and based on our model (to be presented in Section 3), we measure a firm's markup as the ratio of its sales to the cost of goods sold.[7] Figure 1 Panel A displays the aggregate

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

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

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

markup (sales-weighted average) in the economy from 1962 to 2021. The average markup remained around 1.45 during the 1960s and 1970s but reached 1.77 in 2021—a 25% increase from its historical low. Similar trends are observed using alternative markup measures examined in Section 2.5. To further illustrate this shift, we divide our full sample into two periods: the pre-2000 and post-2000 periods.[8] Panel A of Table 1 tests the difference in aggregate markup before and after 2000. The results indicate a significant increase in the aggregate markup across different weighting schemes. Column 1 shows that the equal-weighted aggregate markup rose from 1.61 before 2000 to 1.87 after 2000, representing a 16.1% increase. Columns 2 and 3 reveal similarly significant increases: the asset-weighted average markup grew from 1.60 to 1.93, while the sales-weighted average markup increases from 1.50 to 1.66.

## 2.2 The decline of the value premium

A prominent trend in recent financial markets, as documented by Fama and French (2021), is the sharp decline in the value premium. We confirm this finding in Figure 1 Panel B, which plots the 20-year rolling average value premium over time and reveals a clear declining trend.[9] Table 2 Column 1 reports the average monthly value premium in the economy, measured as the return spread between firms in the top and bottom book-to-market quintiles for the pre- and post-2000 periods. For instance, Panel A column 1 shows that the value premium is both economically large and statistically significant in the pre-2000 period, averaging 0.48% per month with a t-statistic of 2.73. In contrast, Panel B column 1 shows that the value premium becomes negative and insignificantly different from zero in the post-2000 period.

Table 2 Panel C reports the change in the value premium between the two periods. Column 1 shows that the value premium has dropped by around half a percent per month in the post-2000 period. Table 2 Panel D reports the change in the value premium in terms of its CAPM alpha. As the constant in column 1 indicates, the CAPM alpha of the value

the estimated demand elasticity coefficient into the markup calculation does not alter our empirical findings since their measure and ours are highly correlated, as shown in Tables A.4 and A.5 of the Online Appendix.

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

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

premium is 0.55% per month (t-statistic: 3.18) in the pre-2000 period. However, it has declined significantly by 0.86% per month (t-statistic: -2.69), resulting in a negative CAPM alpha in the post-2000 period. In the Online Appendix, we report similar results using alternative measures of the value premium including the decile spread, the HML factor, and the intra-industry value premium.

## 2.3 Linking the two trends

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

We start by showing that the rise in markups is not uniform across all firms. High-markup firms are the primary drivers of this increase, as their markups have grown significantly faster than those of other firms. Figure 2 Panel A provides a time series plot of the average markups for low-markup and high-markup firms from 1962 to 2021, where low- and high-markup firms are defined as those in the bottom and top markup terciles.[10] While the average markup for low-markup firms remains flat throughout the sample period, the markup for high-markup firms exhibits a noticeable and steady increase. We report the change in average markup of low- and high-markup firms in Panel B of Table 1. In this panel, we compute the sales-weighted average markup for each group. Column 1 shows that the average markup of firms in the bottom group remains stable over time. Column 2 reveals that high-markup firms see a substantial rise, with their average markup increasing by 0.54 from 2.10 before 2000 to 2.64 after 2000, representing a 26% increase.[11] Column 3 shows that the difference in markup between the low- and high-markup firms has widened significantly.

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

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

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

markup tercile as the difference in returns between value and growth stocks in that group.[12]

Figure 2 Panel B plots the rolling-average value premium for low- and high-markup firms over time. The value premium remains stable among low-markup firms, while high-markup firms exhibit a clear decline. Table 2 also provides the detailed value premium of low- and high-markup terciles. In the pre-2000 period, Panel A shows that the monthly value premia for low- and high-markup firms are 0.42% and 0.77%, respectively—both statistically significant.[13] The difference between the two groups is not statistically significant, indicating a robust value premium across markup levels before 2000.

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

## 2.4 Productivity disparities across firms with different markups

Complementing the divergent trends in markups and value premiums between low- and high-markup firms, we also identify a growing divergence in their productivity trajectories: in the post-2000 period, high-markup firms exhibit substantially faster productivity growth than low-markup firms. Productivity is measured using the methodology of İmrohoroğlu

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

[13]The returns for all 15 portfolios are reported in Table A.2 in the Online Appendix.

and Tüzel (2014).[14] Figure 2 Panel C displays the evolution of the average productivity for low- and high-markup firms over our sample period. Throughout, high-markup firms maintain a higher productivity level than their low-markup counterparts. Moreover, this gap in productivity widens substantially in the post-2000 era, reflecting divergent growth dynamics between the two groups. In the pre-2000 period, high-markup firms achieved an average annual productivity growth rate of 0.78%, compared to 0.53% for low-markup firms. After 2000, however, high-markup firms accelerate to 0.92% per year, while low-markup firms' growth rate falls to just 0.07%. This growing productivity gap between high- and low-markup firms provides a third piece of the puzzle, suggesting that the divergent trends in markups and the value premium are linked to, and may in part reflect, fundamental differences in firms' technological capabilities.

## 2.5 Robustness checks

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

**Alternative sample periods** 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 other measures of the value strategy. These findings demonstrate that the decline in the value premium is robust to variations in the sample period cutoffs.

**Industry-level analysis** We examine industry-level markup trends and value premium trends. We sort industries into terciles based on their markups and find that industries in the top markup tercile see their average markups rise by over 10 percent in the post-2000 period, whereas those in the bottom tercile exhibit no significant change between the pre-

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

and post-2000 eras. Similar to the firm-level findings, the value premium of industries in the lowest markup tercile remains stable throughout the entire sample period, while the value premium of industries in the top markup tercile becomes statistically insignificant after 2000. These results are presented in Table A.3 of the Online Appendix.

**Alternative markup measures** We also check the robustness of our results using alternative measures of markup. First, we follow the methodology of De Loecker, Eeckhout, and Unger (2020) to measure markup. The difference between their measure and ours is that their measure multiplies the ratio between sales and cost of goods sold by an estimated industry demand elasticity coefficient. We demonstrate that our results are robust to using their measure. Additionally, we consider another alternative definition of the markup. In this definition, we include part of the Selling, General, and Administrative (SG&A) expenses in the variable cost, since the SG&A expense might not be entirely fixed. Our main findings are robust to the use of this alternative markup measure. The results of these exercises are shown in the Online Appendix Tables A.4 and A.5.

**Excluding micro-cap or superstar firms** We also assess the robustness of our findings by excluding micro-cap stocks. Table A.6 Panel A shows that our findings on the cross-sectional decline of the value premium remain the same when we limit our attention to non-micro-cap stocks. Autor, Dorn, Katz, Patterson, and Van Reenen (2020) document the rise of superstar firms and their impact on the aggregate labour share. We find that the markup has risen significantly among both superstar firms and non-superstar firms, as shown in Figure A.2 and Table A.7. In addition, our main findings on the cross-sectional changes in markups are similar among superstar and non-superstar firms.

**Alternative explanations** We analyze several alternative explanations for the decline of the value premium and the rise of markups. The Online Appendix presents the results of these alternative explanations, including the size effect in Section A.2, the rise of superstar firms in Section A.5, the fluctuation of micro-uncertainty in Section A.7, new entries in Section A.9, and how alternative firm-level characteristics, such as profitability and intangible assets, affect the value premium in Section A.8. The overall finding is that these alternative channels do not explain the decline in the value premium.

# 3 Model

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

## 3.1 Setup

The model features a stochastic technology frontier, costly technology adoption, and strategic competition. Moreover, we allow for several sources of heterogeneity in the model: the first is the cross-time difference in the efficiency of the aggregate technology frontier, the second is cross-group heterogeneities, including differences in the benefit (the marginal production cost) and cost of frontier technology adoption, firm demand elasticity, and fixed operating costs in 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.[15] The parameter $\xi$ controls the elasticity of substitution between different products, which we refer to as the firm's demand elasticity. This demand function is consistent with Dixit and Stiglitz (1977) who characterize the structure of the standard monopolistic competition model, and is widely used in the literature, e.g., Aw, Roberts, and Xu (2011), Corhay, Kung, and Schmid (2020) among others.

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

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

where $\eta$ is the 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 than the elasticity of substitution across industries $\xi > \eta$ (Corhay, Kung, and Schmid, 2020).

## 3.3 Production technology

Firms use physical capital ($k_{j,t}$) to produce 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

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

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

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

in which $\varepsilon_{t+1}^{X}$ 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), $\rho_x$ and $\rho_z$, $\sigma_x$ and $\sigma_z$ are autocorrelations and conditional volatilities of aggregate and firm-specific productivities, respectively.

Taking equation (3) and equation (4) 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 $\delta_k$ denotes the capital depreciation rate.

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

## 3.4 Technology frontier and technology adoptions

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

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

in which $s_{t+1} = \log(S_{t+1})$, $\varepsilon_{t+1}^{s}$ is an i.i.d. standard normal shock that is independent of all the other shocks in the economy, and $\rho_s$, and $\sigma_s$ 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 $\delta_n$. 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

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

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

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

$$oc_{j,t} = \begin{cases} \frac{f_o}{S_t} y_{j,t}, & \text{if } \phi_{j,t} = 1 \\ \frac{f_o}{(1-\delta_n) n_{j,t-1}} y_{j,t}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{12}$$

This assumption highlights several ways in which new technologies can enhance firm efficiency by reducing production costs. First, the IT boom from 1995 to 2005 enabled firms to expand into multiple product lines. For example, advancements in cloud storage and computing helped reduce overhead costs associated with entering multiple markets (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023). 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).

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

$$ac_{j,t} = \begin{cases} f_a, & \text{if } \phi_{j,t} = 1 \\ 0, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{13}$$

## 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 $x_t = \log(X_t)$, $r_f$ is the (log) risk-free rate, $\gamma_x > 0$ and $\gamma_s > 0$ are the loadings of the stochastic discount factor on the two aggregate shocks. The risk factor loading parameters ($\gamma_x$ and $\gamma_s$) are positive. The specification $\gamma_x > 0$ is consistent with most equilibrium models (e.g., Jermann (1998)). Low aggregate productivity states are associated with low output and thus low consumption and high marginal utility. The specification $\gamma_s > 0$ 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 demonstrate 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. 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 state variables as $\Theta_t = \left(k_{_{j,t}}, n_{j,t-1}, z_{_{j,t}}; X_t, S_t, \chi_t\right)$. It includes (1) a firm's capital stock, $k_{j,t}$, (2) a firm's technology capital $n_{j,t-1}$, (3) the firm's idiosyncratic productivity, $z_{j,t}$, (4) aggregate productivity, $X_t$, (5) the current value of aggregate technology frontier, $S_t$, (6) the joint distribution of idiosyncratic productivity, and firm-level capital stocks and technological capital, $\chi_t$, which is defined for the space U=$\mathrm{R}_+ \times \mathrm{R}_+ \times \mathrm{R}_+$.

We denote firms' value function by $v_{j,t}\left(\Theta_t\right)$ as 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, physical 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, the equilibrium markups, 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 foundational work of Maskin and Tirole (1988a) and Ericson and Pakes (1995), we focus on the Markov Perfect Equilibrium such that 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 $\chi_t$.
- 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 $Q_t = P_t^{-\eta}$.

### 3.6.2 Equilibrium approximation and strategic interactions

To analyze the dynamics of our monopolistic competition model, we compute the Markov Perfect Equilibrium using the algorithm of Krusell and Smith (1998). This methodology is the standard approach for solving dynamic models with heterogeneous agents, as the full industry state—the joint distribution of capital, technology, and productivity across all firms—is intractably high-dimensional. The algorithm overcomes this curse of dimensionality by assuming that the relevant features of the aggregate economy can be summarized by a small set of state variables.

In our model, firms are non-dominant but interact strategically through their collective impact on aggregate prices. An individual firm's optimal policy depends on its expectation of these aggregate prices, which in turn depend on the investment and technology adoption decisions of all other firms. To make this problem tractable, we assume that the relevant industry state can be summarized by the aggregate capital stock, $K_t = \int_j k_{j,t} dj$ and approximate the law of motion of $K_t$ and $P_t$. This is a natural state variable, as it is the primary endogenous determinant of industry-wide production and, therefore, prices.[16] Firms form rational expectations about the future path of aggregate capital ($K_{t+1}$) and prices ($P_t$) based

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

on the current aggregate state, which consists of the exogenous technology shocks ( $X_t$,$S_t$) and the endogenous aggregate capital stock ($K_t$). The equilibrium is found by iterating until the firms' perceived law of motion for ($K_{t+1}$, $P_t$ ) is consistent with the actual law of motion generated by their collective decisions. This computational framework allows us to capture the essential strategic feedback loop in our industry—whereby firms' actions shape the aggregate environment, which then influences individual firm behavior—while remaining computationally feasible. Online Appendix section C details the numerical procedure of solving the Markov perfect equilibrium.

This setup allows for rich strategic interactions. For example, a higher level of aggregate capital $K_t$ is associated with lower aggregate prices $P_t$, reflecting intensified price competition as firms undercut one another. The strength of this strategic effect is governed by the industry demand elasticity ($\eta$), which plays a key quantitative role in shaping model results. This competitive pressure creates two distinct and opposing effects on firm strategy. First, it creates a *strategic substitution* effect in capital investment: lower expected prices reduce the marginal revenue product of capital, causing firms to invest less. Second, it creates a *strategic complementarity* effect in technology adoption: the prospect of lower prices from intensified competition incentivizes firms to adopt cost-reducing technologies to protect their margins. Section 4.2 provides a detailed analysis of these model-implied strategic investment and technology adoption policies.

## 3.7 Equilibrium markups

It is helpful to contrast our model with the existing literature on equilibrium markups before deriving the model-implied markup. Prior studies typically estimate markups using either a demand-side approach—based on optimal pricing—or a production-side approach, which infers marginal costs from firms' cost minimization problems (e.g., De Loecker, Eeckhout, and Unger (2020)). While our model aligns more closely with the production-side approach, it differs in two important respects.

First, the underlying industrial structure is different. Production approaches assume that firms rent capital at a user cost and purchase variable inputs. In contrast, our model assumes firms (investors) own capital, enabling us to examine asset pricing implications that are not captured in models with rented capital. Second, the assumption of production

costs differs. In the production approach, total costs typically include capital rental and variable inputs, which are not explicit functions of output. As a result, marginal costs must be inferred through a constrained cost minimization problem. By contrast, since firms in our model own their capital, rental costs are absent. We follow the literature on firm dynamics (e.g., Melitz (2003); Dou, Ji, and Wu (2021)) in assuming a linear variable cost function, which implies a constant marginal cost for a given level of adopted technology. This simplification abstracts from cost-side complexities, allowing us to focus on the interaction between endogenous technology adoption and market power in shaping markups and risk premia.

Despite differences in derivation, the model-implied markup in our setting is defined as the ratio of total sales to variable production costs—consistent with the measure in De Loecker, Eeckhout, and Unger (2020) and with the empirical markup used in our data. A distinction is that our formulation avoids the need to estimate output elasticities of variable inputs, as noted in Footnote 7.

Finally, while our model features monopolistic competition, it departs from standard frameworks (e.g., Dixit and Stiglitz (1977)) that typically imply constant markups. Instead, our model endogenously generates variation in markups through firms' technology adoption decisions, which directly affect marginal production costs.

To formalize this, we follow the literature in defining a firm's markup ($\mu_{j,t}$) as the ratio of price to marginal cost. In the model, total costs consist of variable production costs ($oc_{j,t}$), technology adoption costs ($ac_{j,t}$), and fixed operating costs ($f$), i.e., $oc_{j,t}+ac_{j,t}+f$. Marginal cost is thus given by $\frac{\partial(oc_{j,t}+ac_{j,t}+f)}{\partial y_{j,t}}$. Since $oc_{j,t}$ is linear in output $y_{j,t}$, while $ac_{j,t}$ is fixed after a firm decides on technology adoption and $f$ is constant,[17] the marginal cost simplifies to $\frac{\partial(oc_{j,t})}{\partial y_{j,t}}$. It follows that: $\mu_{j,t} = \frac{p_{j,t}}{\frac{\partial\left(oc_{j,t}+ac_{j,t}+f\right)}{\partial y_{j,t}}} = \frac{p_{j,t}}{\frac{\partial\left(oc_{j,t}\right)}{\partial y_{j,t}}} = \frac{p_{j,t}y_{j,t}}{oc_{j,t}}$. Substituting the firm's pricing rule from equation (3), we obtain

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

$$\mu_{j,t} = \begin{cases} \left(z_{j,t}k_{j,t}X_t\right)^{-\frac{1}{\xi}} P_t^{1-\frac{\eta}{\xi}} \frac{S_t}{f_o}, & \text{if } \phi_{j,t} = 1 \\ \left(z_{j,t}k_{j,t}X_t\right)^{-\frac{1}{\xi}} P_t^{1-\frac{\eta}{\xi}} \frac{(1-\delta_n)n_{j,t-1}}{f_o}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{18}$$

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 holding all else constant. 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. This endogenous variation in markups, driven by technology adoption, is what allows our model to speak directly to the empirical patterns we document.

## 3.8 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

$$v_{j,t}\left(\Theta_t\right) = d_{j,t} + E_t\left[M_{t,t+1}v_{j,t+1}\left(\Theta_{t+1}\right)\right] \tag{19}$$

$$\Longrightarrow 1 = E_t\left[M_{t,t+1}r^s_{j,t+1}\right] \tag{20}$$

in which equation (19) is the Bellman equation for the value function, and the Euler equation (20) follows from the standard formula for stock return $r^s_{j,t+1} = v_{j,t+1}\left(\Theta_{t+1}\right)/[v_{j,t}\left(\Theta_t\right) - d_{j,t}]$. Substituting the stochastic discount from equation (15) into equation (20), and some algebra yields the following equilibrium asset pricing equation:

$$E_t\left[r^e_{j,t+1}\right] = \lambda_x \times \beta^{j,x}_t + \lambda_s \times \beta^{j,s}_t \tag{21}$$

in which $r^e_{j,t+1} = r^s_{j,t+1} - R_f$ is the stock excess return, $\lambda_x = \gamma_x Var\left(\triangle x_{t+1}\right)$ and $\lambda_s = \gamma_s Var\left(\triangle s_{t+1}\right)$ are the price of risk of the aggregate productivity shock and aggregate technology frontier 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 (21), the equilibrium risk premiums in the model are determined 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 ($\gamma_x$ and $\gamma_s$) 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.

# 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 results on the value premium and the markups.

## 4.1 Calibration

To examine the rise in markups and the decline of the value premium 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,[18] while in the post-2000 economy, we emphasize heterogeneity 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 3. Because all the firm-level accounting variables in the data are only available at an annual frequency, we time-aggregate the simulated accounting data to make the model-implied

[18] We do not incorporate heterogeneity for the pre-2000 economy because the value premium is not significantly different between low- and high-markup groups of firms over this period as shown in Table A.2.

moments comparable with those in the data. To generate the model's implied moments, we simulate $3,600$ firms for $1,000$ quarterly periods. We drop the first 700 quarters to neutralize the impact of the initial condition. The remaining 300 quarters of simulated data are treated as those from the economy's stationary distribution. We then simulate 200 artificial samples and report the cross-sample average results as model moments.

**Parameters common across the pre- and post-2000 economies**

*Firm's technology.* We set the industry demand elasticity $\eta = 4$ and the capital depreciation rate $\delta_k$ is set to be 3.5% per quarter as in Bloom (2009). Because there is no readily available depreciation rate for technology capital $\delta_n$ in the data, we set it to 4.5% (18% annually), which is within the range of empirical estimates of the depreciation rate for intangible capital in the literature.[19]

*Stochastic processes.* Following Jermann (1998), we set the persistence of the aggregate productivity shock $\rho_x = 0.95$ and the conditional volatility $\sigma_x = 0.01$. Given the volatility of the aggregate productivity shock, we set the persistence of the aggregate technology frontier shock to be $\rho_s = 0.95$ and the conditional volatility to be $\sigma_s = 0.02$ to match aggregate stock market volatility. To calibrate the persistence and conditional volatility of the firm-specific productivity shock, we follow Bloom (2009) and set $\rho_z = 0.95$ and $\sigma_z = 0.15$ so that the model implied cross-sectional dispersion in stock returns is 26%, close to that estimated in Campbell, Lettau, Malkiel, and Xu (2001). We calibrate the 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 and the Sharpe ratio of the market.

**Parameters varying across two economies and markup groups** The key parameter that varies between the pre- and post-2000 economies is the long-run average efficiency of the aggregate technology frontier ($\bar{s}$), which we calibrate following Aghion, Bergeaud, Boppart, Klenow, and Li (2023). Furthermore, we allow for heterogeneity in four key firm-level parameters between the low- and high-markup groups in the post-2000 economy: demand elasticity

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

($\xi$), marginal production cost ($f_o$), technology adoption cost ($f_a$), and fixed operating cost ($f$). Demand elasticity captures firms' market power, while marginal production cost ($f_o$) influences the benefit of technology adoption—lower $f_o$ implies higher gains from adopting new technology given the frontier shocks. Technology adoption cost ($f_a$) directly affects the firm's adoption decision, and fixed operating cost ($f$) affects the firm's net income-to-sales ratio.

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

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

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

To calibrate our measure, we align the keyword count threshold with the average technology adoption rate for the post-2000 period. Drawing on the European Investment Bank (EIB) Investment Survey, which reports that 71% of companies in the US adopted some type of advanced digital technologies in 2022, we set a threshold of 45 keyword mentions to identify whether a firm adopts the new technology. This threshold results in approximately a 70% adoption rate in our sample in the post-2000 period.[20] For robustness, we replicate this exercise for the pre-2000 period and find an average adoption rate of 42%, consistent with lower technological penetration during this era.

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

## 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 4 Panel A illustrates firms' technology adoption decisions as a function of technology capital ($n$), considering different levels of aggregate productivity, the aggregate technology frontier, and idiosyncratic productivity, while holding all other state variables at their long-run average values. The figure shows that firms are more likely to adopt the frontier technology when aggregate productivity ($X$), the technology frontier ($S$), or firm-specific productivity ($z$) is higher. This result is intuitive: higher productivity levels are associated with greater expected benefits of adoption, primarily through a higher expected marginal product of physical capital. Additionally, a more advanced technology frontier directly lowers marginal production costs, further increasing incentives for adoption. Furthermore, when a firm's current technology capital is low and far from the frontier, adoption is more likely because the benefits of upgrading outweigh the adoption cost. In contrast, firms with high technology capital, already close to the frontier, choose not to

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

adopt, as the benefits no longer justify the adoption costs.

Recall that the aggregate capital $K_t$ 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 $P_t$, reflecting increased price competition as firms undercut each other. To examine the effects of strategic competition in the model, Figure 4 Panel B plots the policy functions and value functions against either firm-level physical capital ($k_t$) or technology capital ($n_t$), varying the aggregate price level, $P_t$.

The policy functions in Figure 4 reveal the strategic trade-offs firms face. The top-left panel illustrates the physical investment decision. As expected, a firm's investment rate is decreasing in its own capital stock, reflecting diminishing returns in the revenue function. More importantly, the figure reveals a significant strategic effect: when the aggregate price level, $P$, is low—indicating a market with high aggregate capital and intense competition—firms reduce their investment. This occurs because lower market prices reduce the marginal revenue product of capital, creating a *strategic substitution* effect: when competitors undercut prices, firms have an incentive to invest less. As the bottom-left panel confirms, this intensified competition unambiguously erodes firm value.

The top-right panel reveals a contrasting dynamic for the technology adoption decision. Unlike physical investment, technology adoption exhibits *strategic complementarity*. When faced with declining aggregate prices due to rising competition, firms become more likely to adopt the frontier technology. The intuition is that adoption provides a crucial competitive advantage: by lowering its marginal production costs, a firm can better defend its margins against industry-wide price pressure. However, while this cost-reduction motive is strong, it does not fully offset the negative impact of a lower price environment on revenues. Consequently, as shown in the bottom-right panel, overall firm value still declines as competition intensifies, even for firms that choose to adopt.

Figure 5 illustrates the model-implied markups as a function of the scaled aggregate technology frontier ($\frac{S_t}{\max S_t}$). In the pre-2000 economy, when the technology frontier is low (indicating low efficiency), firms are less likely to adopt new technology, as the cost-reduction benefits are minimal, resulting in no change in markups. However, when the technology frontier is high (indicating high efficiency), the benefits of technology adoption become significant due to greater reductions in marginal production costs. Consequently, firms choose to adopt the frontier technology, leading to an increase in markups. Comparing the pre- and post-

2000 economies, firms in the low-markup group in the post-2000 economy experience lower markups. This is driven by higher marginal production costs ($f_o$) and lower market power, reflected in higher firm demand elasticity ($\xi$); the detailed calibration will be discussed in subsection 4.3. In contrast, firms in the high-markup group exhibit larger markups and higher adoption rates, benefiting from lower marginal production costs and greater market power.

## 4.3 Main quantitative results

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

### 4.3.1 Pre-2000 economy

In the pre-2000 economy, we simplify the analysis by setting the mean level of the technology frontier to 1, implying $\bar{s} = 0$. We set the firm demand elasticity $\xi = 5$, marginal production costs $f_o = 0.19$, the adoption cost $f_a = 7.8$ and the fixed operating 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. Notably, the model replicates observed magnitude of markups through the joint effects of firms' market power and their technology adoption decisions. It also aligns well with main asset pricing moments, as reported in Table 4. The model-implied market return and risk-free rate are 6.20% and 2%, respectively, closely matching the data moments of 6.05% and 2.06%. The model's Sharpe ratio is 0.39, same as the observed value of 0.39.

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

Importantly, the model generates a substantial value premium of 5.12%, which is close to the observed value of 5.74% in the data. In the model, value firms are those with low idiosyncratic productivity ($z_{j,t}$), outdated technology capital ($n_{j,t-1}$), and are less profitable. They generate lower current dividends and have lower expected future cash flows, resulting

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

#### 4.3.2 Post-2000 economy

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

To capture the heterogeneity between low- and high-markup groups, we calibrate the firm demand elasticity ($\xi$), 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 ($\xi$), indicating greater market power. They also incur lower marginal production costs ($f_o$), which implies greater benefits from technology adoption and higher production efficiency. This results in a higher likelihood of adopting the frontier technology, with an adoption rate of 81% in the model, despite higher

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

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

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

# 5 Inspecting the mechanism

In this section, we 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 5 reports the result (the row "More efficiency increase in frontier"). We

find that the markup of low-markup firms rises to 1.38, larger than 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 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 due to small changes in marginal production costs relative to the post-2000 baseline low-markup group.

## 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, $\xi$. To analyze the impact of heterogeneity in firm market power, we set the demand elasticity $\xi$ 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 5. 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. Moreover, 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 firm 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 markups and the value premium, 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 operating costs than the high-markup group.) The results of this counterfactual scenario are presented in the row labeled "Shutting down heterogeneity in marginal production costs $f_o$" in Table 5. 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 production 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 markups and the value premium, 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 5 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 5

reports the result. We find that the net-income-to-sales ratio for high-markup firms increases from 0.09 to 0.28. However, the markup, technology adoption rate, and value premium remain largely 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 $\gamma_x$ and $\gamma_s$ 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 Table 5 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 net income-to-sales 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: $rev_{_{j,t}} = P_t^{1-\frac{\eta}{\xi}} \left(X_t z_{j,t} k_{j,t}\right)^{1-\frac{1}{\xi}}$. The term $1-\frac{\eta}{\xi}$ governs the sensitivity of revenues to aggregate prices. To assess the role of strategic interactions, we focus on industry demand elasticity ($\eta$), given the pre-calibrated $\xi$. A higher industry demand elasticity ($\eta$) makes the aggregate price more elastic, thereby

diminishing the influence of strategic interactions on firms.[21] Specifically, we increase $\eta$ 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 $\eta$ from 4 to 6 for the low markup group. The row "Weaker strategic competition" in Table 5 shows that the value premium for low-markup firms falls sharply in the post-2000 period, from 5.34% to 0.18%. This reflects reduced exposure to frontier shocks as industry prices become less sensitive to aggregate fluctuations, lowering risk dispersion. At the same time, their adoption rate and net income-to-sales ratio rise from 0.62 and 0.03 to 0.90 and 0.14, indicating stronger incentives to adopt technology. High-markup firms also experience modest increases in markups, adoption, and profitability, though the effects are smaller given their already limited strategic interaction.

# 6 Aggregate implications and testing of the technology adoption channel

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

## 6.1 Empirical tests of the technology adoption channel

According to our model, the rise of markup and the decline of value premium are concentrated among companies that are most likely to adopt new technologies. To test this channel more directly, we identify those firms through textual analysis by counting the appearance of technology-related keywords in a firm's annual reports.[22] We consider firms that mention these keywords most frequently in their 10-K filings as most likely to adopt new technologies.

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

[22] 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.

To demonstrate how technology adoption affects markup and value premium, we sort firms into different 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.[23] We then sort firms within each size group into terciles based on how many times technology-related keywords appear in their annual reports. We label firms in the top and bottom terciles as high- and low-technology-adoption firms. We then measure these firms' average markup, productivity, and value premium.

Figure 6 Panel A plots the average markup of firms in the low- and high-technology adoption groups. Along with Table 6 Panel A, it shows that high-technology-adoption firms experienced the largest increase in markups—from 1.65 in 1994 to 2.22 in 2021—while low-technology-adoption firms saw little change in their markup over the same period. Table 6 Panel B reports the value premium within low- and high-technology-adoption firms during the post-2000 period. Firms in the bottom technology adoption group continue to have a sizable value premium, at 0.65% per month (t-statistic: 2.21), while the value premium of firms in the highest technology adoption group is close to zero and statistically insignificant. The difference in their value premium is -0.57% per month (t-statistic: -1.72). Additionally, Figure 6 Panel B plots the average productivity of firms in the low- and high-technology adoption groups. It shows that high-adoption firms have consistently higher productivity levels and faster productivity growth over the past 25 years, whereas the productivity of low-adoption firms has stagnated. Overall, these findings support the model's main channel: technology adoption plays a central role in explaining both the rise in markups and the decline of the value premium across firms.

## 6.2 Implications for aggregate productivity growth slowdown

It has been well-documented that total factor productivity (TFP) growth has slowed significantly over the past two decades. The literature offers several explanations for this phenomenon, including a decline in creative destruction due to rising R&D costs (Aghion, Bergeaud, Boppart, Klenow, and Li, 2023) and an increase in entry costs for intangible-intensive firms (De Ridder, 2024), among others. Our model identifies a novel channel

[23] 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.

contributing to this slowdown: capital misallocation arising from systematic differences between low- and high-markup firms. Specifically, heterogeneity in two dimensions—marginal production costs and market power—creates inefficiencies in capital allocation, affecting aggregate productivity.

Recall that in our baseline calibration, low-markup firms face higher marginal production costs and exhibit lower market power (i.e., higher demand elasticity) than high-markup firms. Following Khan and Thomas (2013), we investigate the impact of these two frictions on measured total factor productivity (TFP), since measured TFP reflects the degree of capital misallocation within a group and thus helps us interpret our results. Intuitively, economic frictions prevent some firms—particularly the most productive—from reaching their frictionless optimal capital levels. Consequently, less-productive firms come to hold a disproportionately large share of aggregate capital relative to their productivity, which in turn reduces measured TFP. In the baseline calibration, measured group TFP diverges in the post-2000 economy, with high-markup firms attaining significantly higher productivity.[24] This prediction is corroborated in the data: high-markup firms consistently outperform their low-markup counterparts in average measured productivity.

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

Lastly, turning to the growth rate, in a simulated impulse-response analysis, Figure 7 compares aggregate TFP under each counterfactual scenario to the baseline calibration following a positive technology-frontier shock.[25] When marginal production costs are equalized

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

[25] We simulate the impulse responses of the baseline model and alternative models that exclude cross-group heterogeneities in firm demand elasticity and marginal production costs. Specifically, we run 500 simulations, each spanning 230 periods. In period 201, we introduce a one-time shock by increasing the aggregate technology frontier to its high level and then allow the model to evolve as before. This setup

at low levels, a positive technology frontier shock raises aggregate productivity to grow by 1.3% above the baseline. Conversely, when firms across markup groups share identical high market power (i.e., low demand elasticity), aggregate productivity falls by 0.7% relative to the baseline, reflecting exacerbated capital misallocation after the shock. These results underscore that the interplay of marginal production cost heterogeneity and market power disparities is a critical driver of sluggish TFP. Policy interventions aimed at reducing structural barriers—such as high marginal production costs for low-markup firms (subsidies for low-markup firms' technology adoption) and high market power among high-markup firms (antitrust reforms)—could mitigate misallocation and revitalize productivity.

# 7 Conclusion

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

This paper bridges macroeconomic, financial, and industrial organization perspectives. For macroeconomics, we provide an industry equilibrium model linking markup dynamics and productivity trends to heterogeneity in technology adoption and market power. Embedding this heterogeneity into DSGE models will further illuminate how technology shocks and

enables us to analyze the response to a one-period impulse and its gradual decay over time. To measure the impact, we compute the sales-weighted total factor productivity (TFP) for each group and then take a weighted average of them to obtain the economy-wide aggregate TFP.

market power interact over business cycles, deepening our understanding of contemporary economic challenges. For finance, we connect the value premium's decline to shifts in firms' risk exposure driven by technology adoption. For industrial organization, we emphasize how strategic adoption decisions reinforce value premium and market power disparities. These insights underscore the importance of studying markup and asset price trends jointly to fully grasp their interplay. Our findings have direct policy implications. Interventions aimed at reducing structural barriers—such as subsidizing technology adoption for low-markup firms and curbing anticompetitive practices among high-markup incumbents—could mitigate capital misallocation and revive productivity growth.

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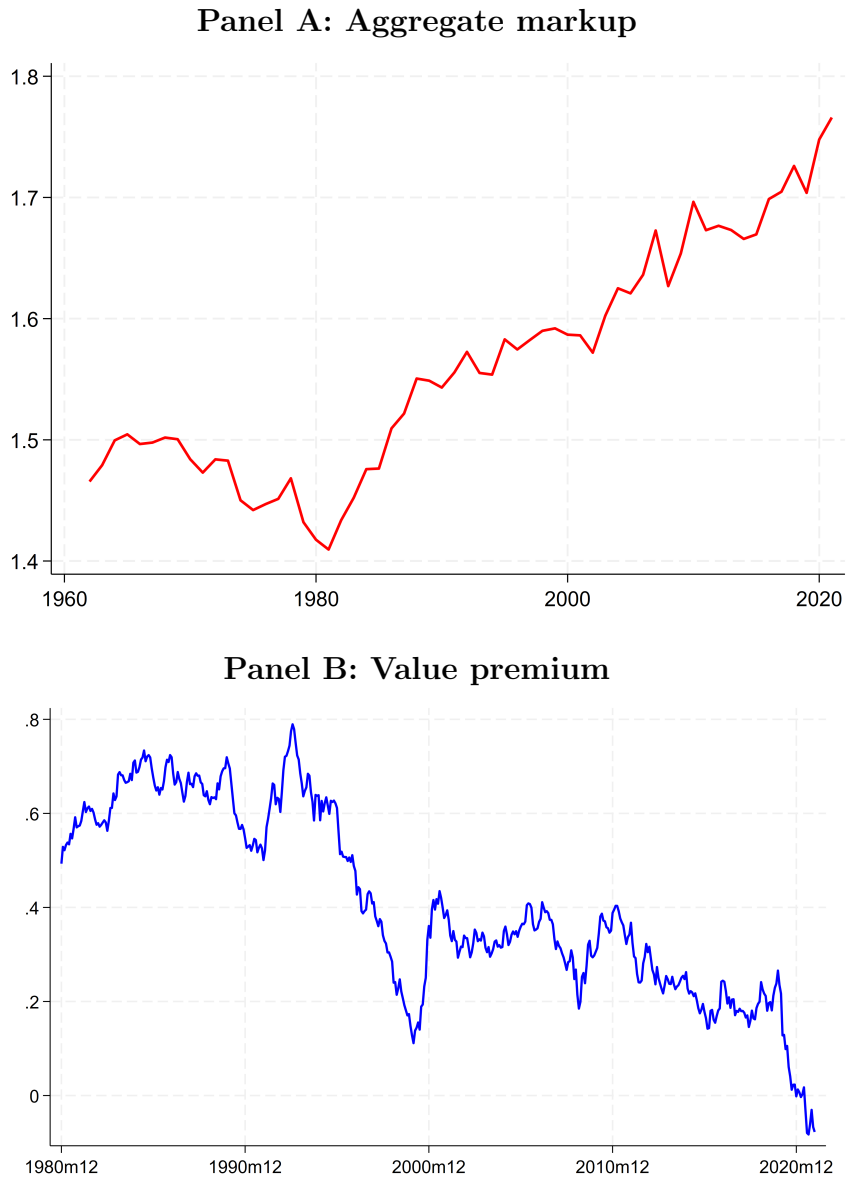
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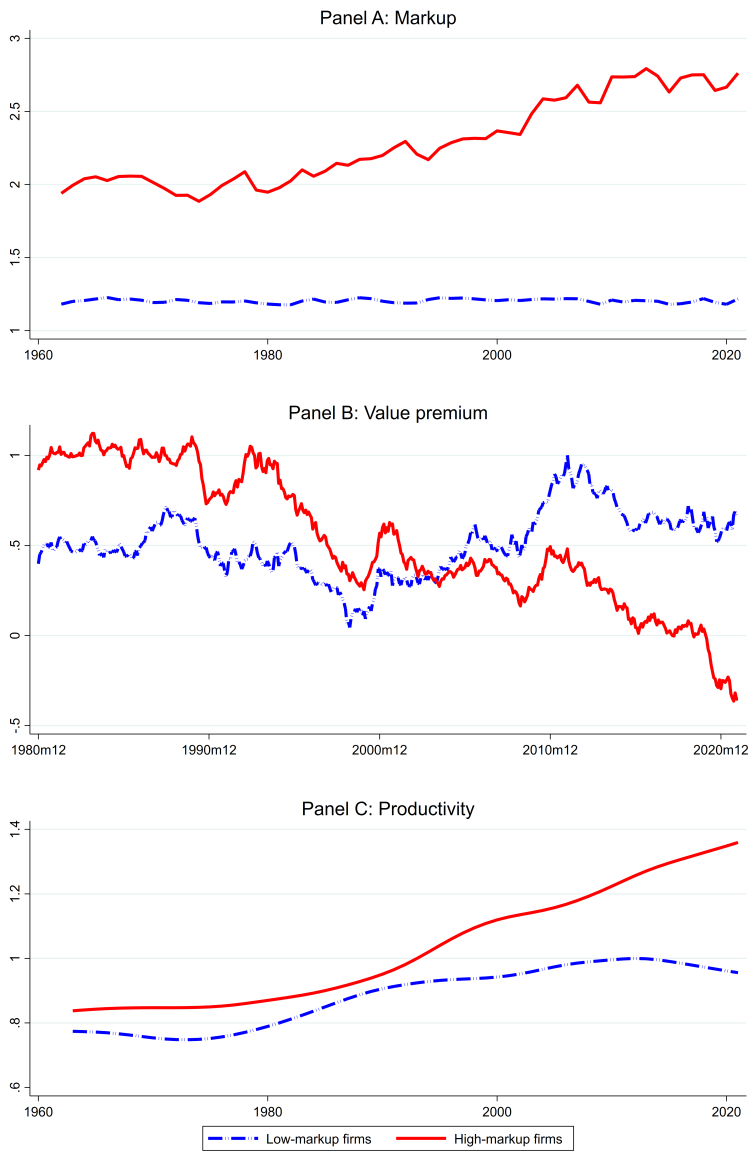
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**Figure 1: Aggregate markup and value premium trends**



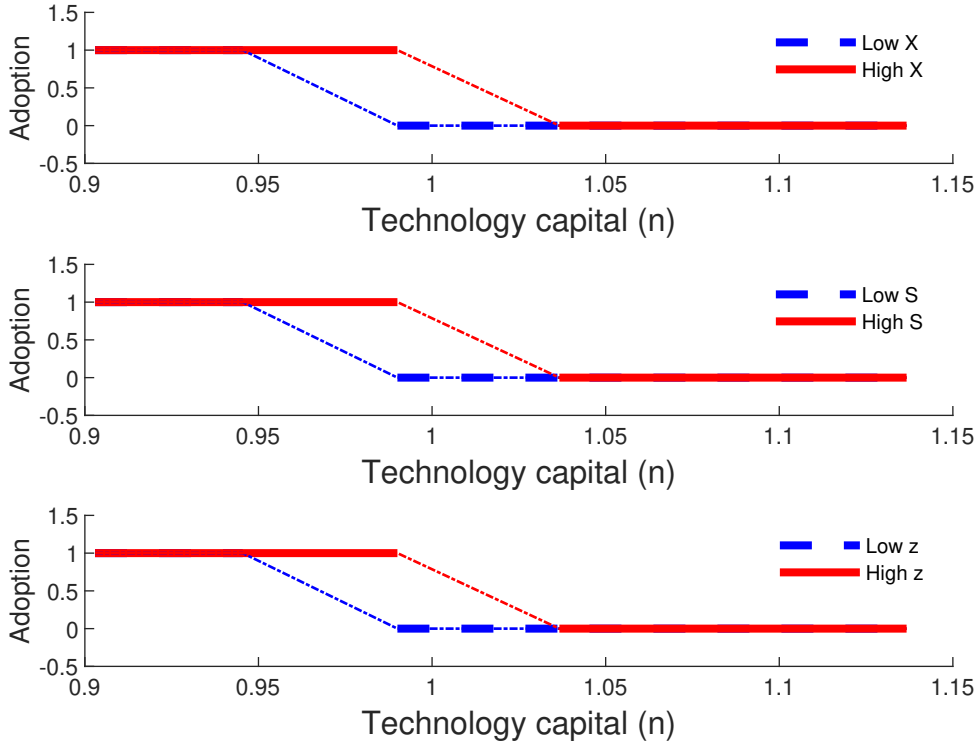

**Notes:** Panel A plots the aggregate (sales-weighted average) markups of US public firms, excluding utilities and financial companies. We measure a firm's markup annually as the ratio of its sales to the cost of goods sold. Panel B shows the 20-year backward rolling average of the monthly value premium,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

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



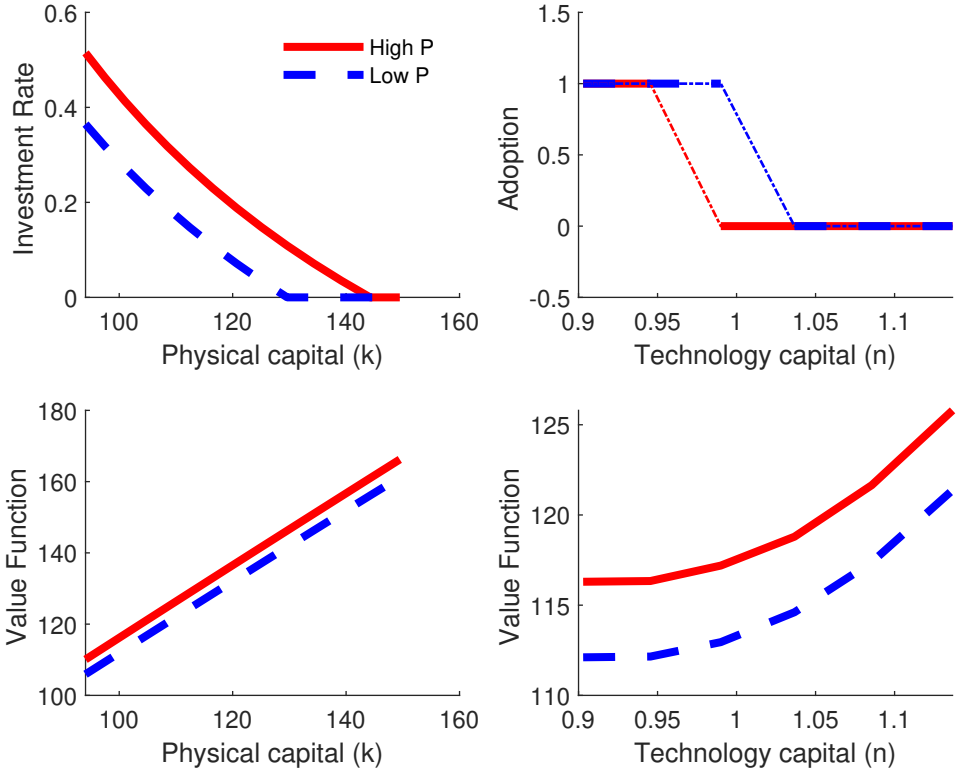

**Notes:** Panel A plots the sales-weighted average markup of low-markup firms (blue-dashed) and high-markup firms (red-solid). Panel B plots the 20-year (backward) rolling average value premium for high- and low-markup firms. The value premium is the return of value stocks minus that of growth stocks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

**Figure 3: Technology adoption policy functions**



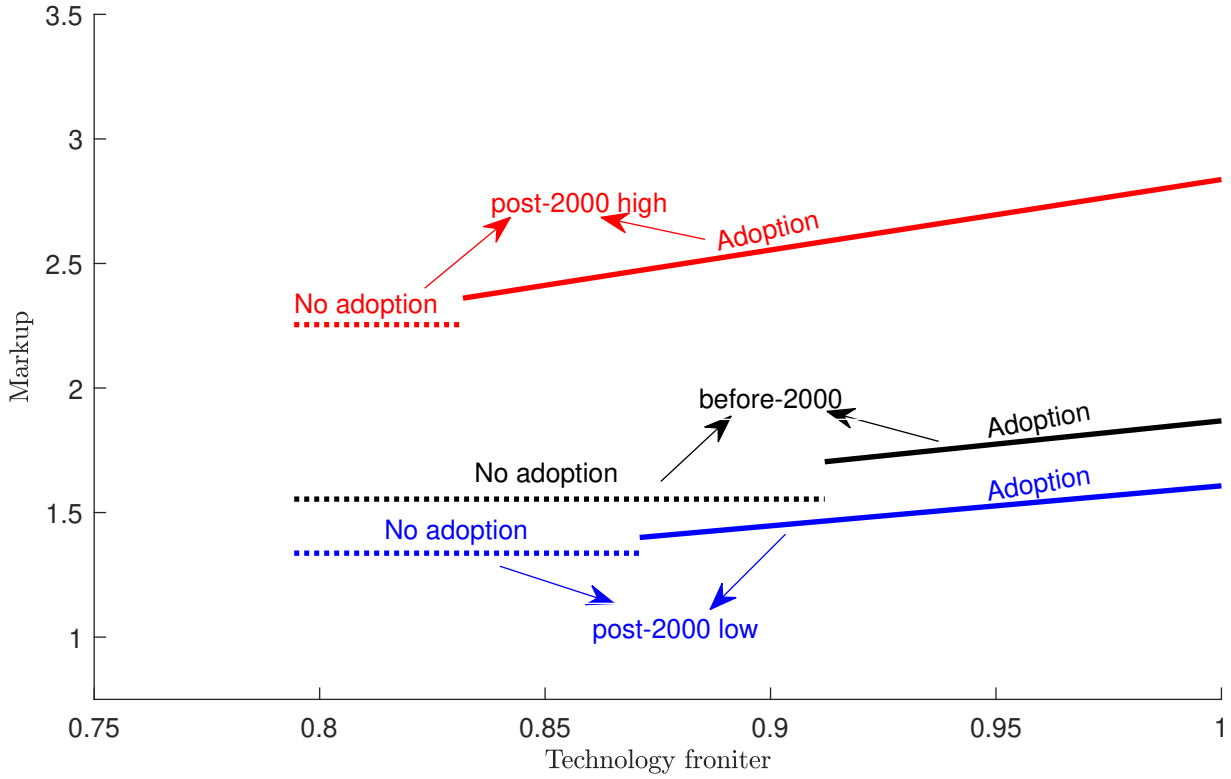

**Notes:** This figure plots the technology adoption decisions as a function of the technology capital ($n$) under the pre-2000 economy calibration. The three panels depict adoption policies with different levels of aggregate productivity $X$ (top), technology frontier productivity $S$ (middle), and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

**Figure 4: Policy functions, value functions, and strategic interactions**



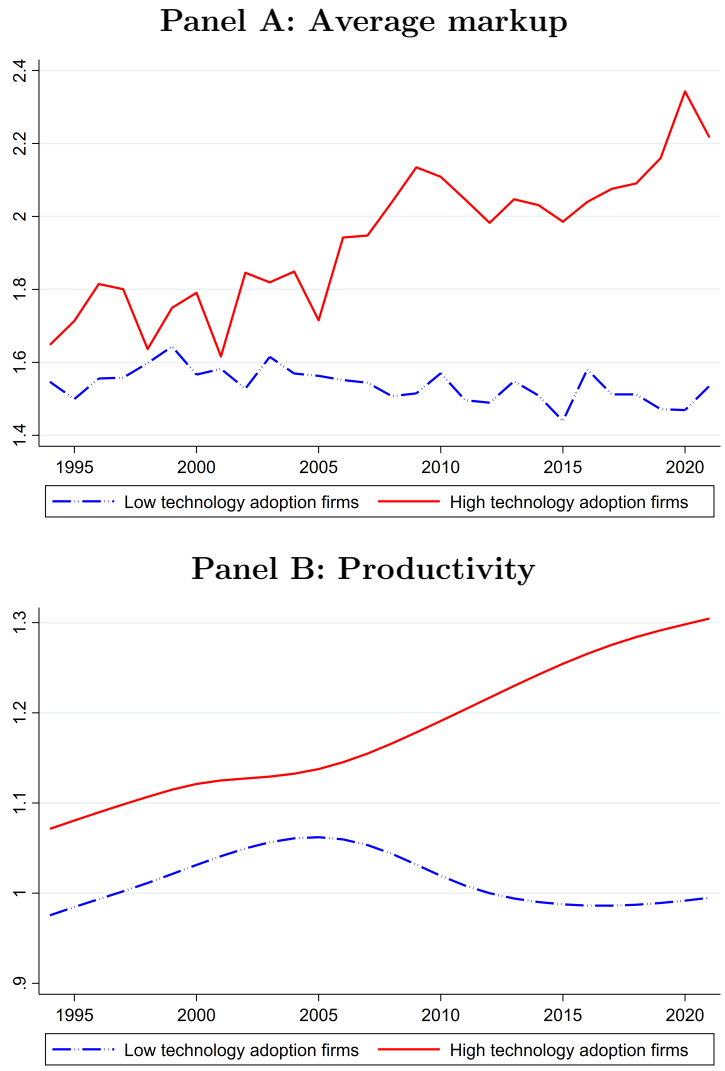

**Notes:** This figure plots the policy functions and value functions as functions of either physical capital ($k$) or technology capital ($n$), with different values of aggregate price $P$ under the pre-2000 economy calibration, while other state variables are fixed at the long-run mean of the corresponding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

**Figure 5: Model implied markups**



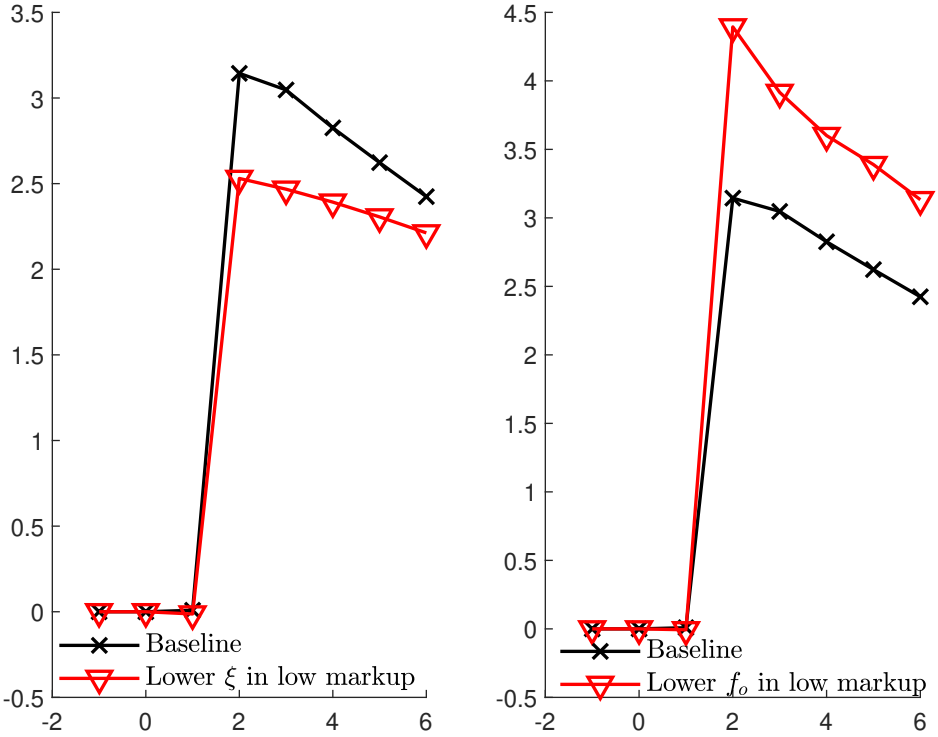

**Notes:** This figure plots model implied markups as a function of the scaled technology frontier, $\frac{S_t}{\max S_t}$, under various calibrations. The black lines correspond to the pre-2000 economy, while the blue and red lines represent the low-markup and high-markup groups in the post-2000 economy,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

**Figure 6: Markup, productivity, and technology adoption**




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

**Figure 7: Aggregate implications for productivity**




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

**Table 1: Increase in markups**

**Panel A: Aggregate markup**

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

**Panel B: Average markup in different groups**

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

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

**Table 2: Decline in the value premium**

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

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

**Table 3: Parameter values**

| A: Common Parameters | | |
|---|---|---|
| Parameter | Symbol | Value |
| ***Technology: general*** | | |
| Industry demand elasticity | $\eta$ | 4 |
| Rate of depreciation for physical capital | $\delta_k$ | 0.035 |
| Rate of depreciation for technology capital | $\delta_n$ | 0.045 |
| ***Stochastic processes*** | | |
| Persistence of aggregate productivity | $\rho_x$ | 0.95 |
| Conditional volatility of aggregate productivity | $\sigma_x$ | 0.01 |
| Persistence coefficient of firm-specific productivity | $\rho_z$ | 0.95 |
| Conditional volatility of firm-specific productivity | $\sigma_z$ | 0.15 |
| Persistence of aggregate technology frontier | $\rho_s$ | 0.95 |
| Conditional volatility of aggregate technology frontier | $\sigma_s$ | 0.02 |
| ***SDF*** | | |
| Real risk-free rate | $r_f$ | 0.005 |
| Loading of the SDF on aggregate productivity shocks | $\gamma_x$ | 4 |
| Loading of the SDF on aggregate technology frontier shocks | $\gamma_s$ | 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 | $\xi$ | 5 | 8 | 4.1 |
| Marginal production costs | $f_o$ | 0.19 | 0.25 | 0.04 |
| Technology adoption costs | $f_a$ | 2.37 | 1.63 | 7 |
| Fixed operating costs | $f$ | 5.68 | 4.01 | 255 |

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

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

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

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

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

| Low markup group | | | | | High markup group | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Markup | Adoption | FC/S | NI/S | V.P. | Markup | Adoption | FC/S | NI/S | V.P. |
| 0. Data | | | | | | | | | |
| 1.20 | 0.61 | 0.10 | 0.03 | 7.44 | 2.63 | 0.82 | 0.23 | 0.09 | -3.60 |
| 1. Baseline model | | | | | | | | | |
| 1.34 | 0.62 | 0.11 | 0.03 | 5.34 | 2.66 | 0.82 | 0.20 | 0.09 | 0.15 |
| 2. More efficiency increase in frontier ($\uparrow \bar{s}$) | | | | | | | | | |
| 1.38 | 0.77 | 0.08 | 0.07 | 0.15 | 2.84 | 0.83 | 0.17 | 0.13 | 0.07 |
| 3. Shutting down heterogeneity in firm demand elasticity $\xi$ ( $\downarrow \xi$ 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 $\eta$) | | | | | | | | | |
| 1.36 | 0.90 | 0.01 | 0.14 | 0.18 | 2.67 | 0.83 | 0.18 | 0.11 | 0.01 |

**Notes:** This table presents selected moments of the data and alternative calibrations of the model for the post-2000 economy, showing the average markup (Markup), technology adoption rate (Adoption), fixed cost-to-sales ratio (FC/S), net income-to-sales ratio (NI/S), and value premium (V.P.). Specification 0 reports the data, while specification 1 presents the baseline calibration of the low-markup group and the high-markup group in the post-2000 economy. Specification 2 increases the aggregate technology frontier efficiency ($\bar{s}$) by 50% compared to the baseline calibration. Specification 3 sets firm demand elasticity ($\xi$) 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 ($\gamma_x$) to zero, while specification 8 sets the risk price of aggregate technology frontier shocks ($\gamma_s$) to zero. Specification 9 increases the industry demand elasticity $\eta$ for both groups.

**Table 6: Technology adoption, markup, and value premium**

**Panel A: average markup**

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

**Panel B: post-2000 value premium**

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

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

# Internet Appendix

## A Additional empirical analysis

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

### A.1 Alternative sample periods

We first examine the decline of the value premium in alternative sample periods. Table A.1 presents the results for the top-minus-bottom book-to-market quintile returns, the top-minus-bottom book-to-market decile returns, the Fama-French HML factor, and the intra-industry value premium.[26] Panel A presents the value premium after 1993, a year in which Fama and French (1993) published their influential paper on the three-factor model. Interestingly, in the post-1993 period, the value premium is no longer significant and is close to zero. The average HML factor return is less than 1% per year since 1993. Panel B reports the value premium after the financial crisis from 2011 to 2021. The average return is highly negative, although statistically insignificant. This period experiences an especially poor performance in the value premium. Anecdotal evidence suggests that the value premium suffered tremendously during the Covid-19 pandemic period. We exclude the Covid-19 period in panel C and report the value premium from 2001 to 2019. Panel C shows that even before the pandemic, the value premium has already disappeared.

### A.2 Size effect

It is well established that the value premium is lower among large-cap companies than small-cap companies. This section tests whether the rise of markups and the decline of the value premium are only observed among large-cap companies. We find that this is not the case. Even among small-cap companies, we observe that their average markup has risen and their value premium has declined. We show these findings in Figure A.1. We classify firms

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

as large-cap or small-cap based on whether their market capitalization is above or below the NYSE median. Panel A of Figure A.1 shows that the average markup of both large- and small-cap companies has risen steadily over the past decades. The pre-2000 sales-weighted average markups of large- and small-cap companies are 1.52 and 1.40, respectively. In the post-2000 period, the average markups of large- and small-cap companies have increased to 1.69 and 1.51, respectively.

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

## A.3 Measuring markups at the industry level

In our main specification, we measure markups at the individual firm level. As a robustness check, we measure markups at the industry level. Specifically, we measure the industry sales and cost of goods sold as the total sales and cost of goods sold of all firms in the same industry. We take the ratio between the two as the industry markup and apply the same industry markup to all firms within the industry. We use 2-digit Standard Industrial Classification codes to define industries. We sort these industries into terciles each year. Table A.3 Panel A regresses the average markup of industries in the top and bottom terciles on the post-2000 dummy variables. It shows that the average markup of low-markup industries remains constant in the two periods, whereas the average markup of high-markup industries increases significantly. Table A.3 Panels B and C report the value premium of stocks in the low- and high-markup industries in the pre- and post-2000 periods. Similar to our main results, in the pre-2000 period, the value premium is significant in both low- and high-markup terciles. The difference in value premium between the two groups is not significant in the pre-2000 period. On the other hand, in the post-2000 period, the value premium in the low-

markup industries remains significantly positive, whereas the value premium of high-markup industries has disappeared.

## A.4 Alternative markup measures

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

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

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

We check whether our result that the value premium remains strong among low-markup firms is robust to measuring markups with SG&A and excluding micro-cap stocks. In Table A.4 Panel B, we sort firms into terciles based on the alternative markup definition. In this definition, we include parts of Selling, General, and Administrative (SG&A) expenses into

the marginal cost. Panel B shows that the value premium remains economically large and statistically significant in the low-markup tercile in the post-2000 period using this alternative markup definition.

Table A.5 Panel B Columns 1 to 3 show that the average markup based on this definition also increased significantly in the post-2000 period. Panel B Columns 4 to 6 show that the increase in markup is mainly driven by firms in the mid- and high-markup terciles, consistent with our main findings.

## A.5 The rise of superstar firms

Another alternative explanation related to the size effect is the rise of superstar firms. Autor, Dorn, Katz, Patterson, and Van Reenen (2020) describe superstar firms as those with the highest productivity in an industry and capturing the most market share. They propose that the rise of superstar firms is an important explanation of the decline of the labor share in the United States. Given that the labor share and markup are theoretically related, in this section, we test whether the rise of superstar firms is the primary driver of our results. We find that this is not the case. Following Autor, Dorn, Katz, Patterson, and Van Reenen (2020), we identify superstar firms as the largest 100 non-finance companies by sales each year. Figure A.2 Panel A shows the trend of the average markup of superstar and non-superstar firms. The two groups of firms have similar trends in their markups. Figure A.2 Panel B shows the value premium of superstar and non-superstar firms, both displaying a declining trend over time. Therefore, we do not find evidence that superstar firms are the only firms driving the rise of the aggregate markup and the decline of the value premium.

Table A.7 Panel A reports the change in the markup of superstar and non-superstar firms in the post-2000 period. We compute the average markup using different weights, such as asset-weighted, equal-weighted, and sales-weighted averages. Columns 1 to 3 show that the average markup of superstar firms increased significantly in the post-2000 period. Similarly, columns 4 to 6 show that the markup of non-superstar firms also increased significantly. Panel B reports the change of the markup of different markup terciles among superstar firms and non-superstar firms. These results are similar to our baseline findings. Most of the increase in markups is concentrated among high-markup firms, regardless of whether they are superstar or non-superstar firms.

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

We show that our findings about the cross-sectional value premium trend is not driven by micro-cap stocks or superstar stocks. In Table A.6 Panel A, we exclude micro-cap stocks when we measure the returns of BM and markup-sorted portfolios. We define micro-cap stocks as those in the bottom NYSE size decile. Panel A shows that the value premium remains significantly positive among low-markup firms in the post-2000 era, whereas the value premium of mid- and high-markup firms is not significant, consistent with our main findings. In Table A.6 Panel B, we exclude superstar firms, defined as the 100 firms with the highest sales each year. Similar to Panel A and our main findings, low-markup firms continue to have significantly positive value premium in the post-2000 period, whereas mid- and high-markup firms no longer have significant value premium.

## A.7 Trend in micro uncertainty

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

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

Figure A.3 Panel B plots the raw micro uncertainty index to highlight its trend. There is

no noticeable decline in the long-term trend of micro uncertainty. If anything, the long-term trend of micro uncertainty appears to be increasing, which does not explain the decline in the value premium.

## A.8 Alternative firm characteristics

We also examine whether alternative firm-level characteristics—such as profitability and intangibles—can account for the decline of the value premium. First, we find that the cross-sectional correlations between markups and various other firm characteristics are low as shown in Table A.8. For example, the correlation of markup with size is only 9%, with book-to-market ratio -14%, with profitability 12%, and with R&D expenditure 14%. The correlations with knowledge capital, organizational capital, and total intangibles are 8%, 11%, and 13%, respectively.[27] These results suggest that markups capture a distinct dimension of firm heterogeneity not spanned by other characteristics.

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

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

We verify if the rise of the aggregate markup is driven by the entry of new firms. We find that this is not the case. Specifically, we remove firms that are less than 3 years old, 5 years old, or 10 years old from our sample and then check the aggregate change in the average markup of the remaining firms. We proxy a firm's age based on the first year it appeared in our dataset. Table A.10 reports the results. In each panel, columns 1 to 3 show the change of the equal-weighted, asset-weighted, and sales-weighted average markup of firms. They all

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

show that the markup increased significantly in the post-2000 period. For example, even in Panel C, where we only focus on firms that are at least 10 years old, their average markup increased significantly and the magnitude of the increase is similar to Table 1. Columns 4 to 6 show that the increase in markup is mainly driven by firms in the mid-, and high-markup terciles, consistent with our main findings.

# B Estimation of technology adoption rates

This section provides more detailed descriptions of how we compute and calibrate companies' rate of technology adoption. To measure the likelihood of a company to adopt new technologies, we apply textual analysis to the company's annual reports. We obtained the cleaned text data of 10-K filings of publicly traded US firms from Loughran-McDonald website.[28] The data starts from 1994, which marks the beginning of our textual analysis. We link the text data with COMPUSTAT using the CIK-GVKEY link table from SEC Analytics Suite by WRDS.

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

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

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

# C Numerical Algorithm

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

## C.1 Solving the monopolistic competitive equilibrium

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

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

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

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

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

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

Now we describe our solution algorithm details. We first initialize the forecast rules $\hat{\Gamma}_P^{(1)}$ and $\hat{\Gamma}_K^{(1)}$ with guessed initial coefficients $\alpha_P^{(1)}(X,S)$ and $\beta_P^{(1)}(X,S)$, and $\alpha_K^{(1)}(X,S)$ and $\beta_K^{(1)}(X,S)$. 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 $\epsilon_\Gamma$, 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 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 $\mathrm{i} = 1, \ldots, \mathrm{n_k n_n n_z}$ and $\prod \left(z_i, z'_j\right)$ is the transition matrix for firm-specific productivity.

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

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

$$\log\left(p_t\right) = \alpha_p\left(X_t, S_t\right) + \beta_p\left(X_t, S_t\right)\log\left(K_t\right)$$
$$\log\left(K_{t+1}\right) = \alpha_K\left(X_t, S_t\right) + \beta_K\left(X_t, S_t\right)\log\left(K_t\right).$$

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

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

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

where $\epsilon = 1\%$.

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

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

## C.2 Solving the Bellman equation

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

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

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

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

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

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

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

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

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:

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

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

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

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

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

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

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

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

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

Under the case $\phi_t = 0$, their technology capital depreciates at the rate of $\delta_n$. 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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

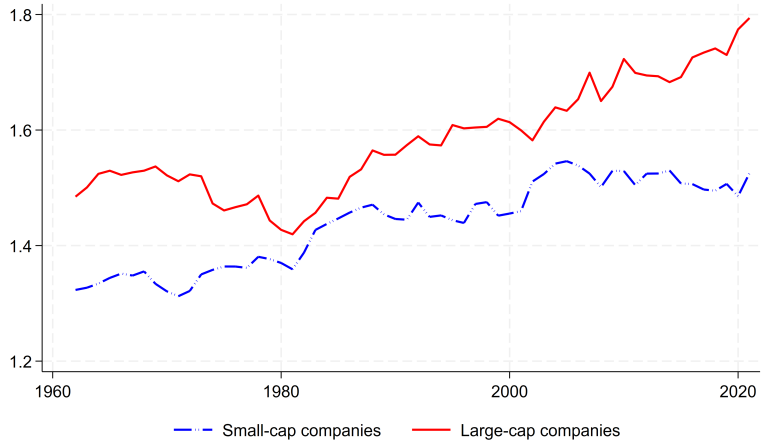
After we solve these two cases, we let

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

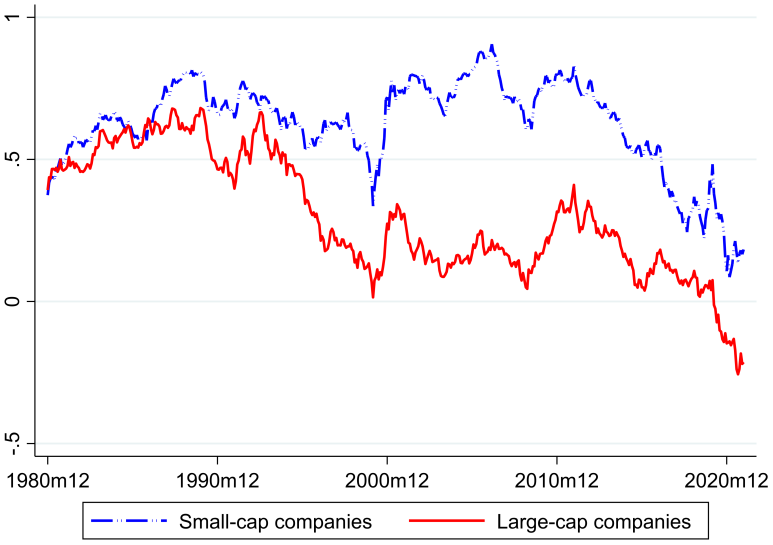
which will tell us whether $\phi_t\left(k_t, n_{t-1}, z_t, X_t, S_t, K_t\right)$ is 0 or 1.

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

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



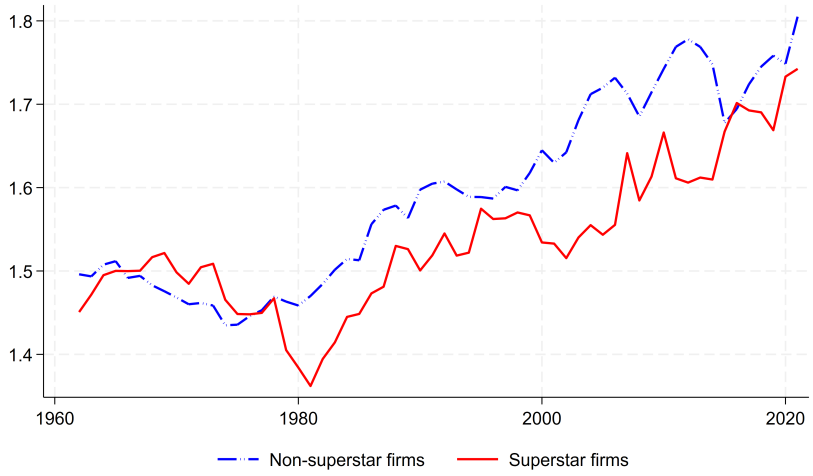

### Panel B: value premium among large- and small-cap companies



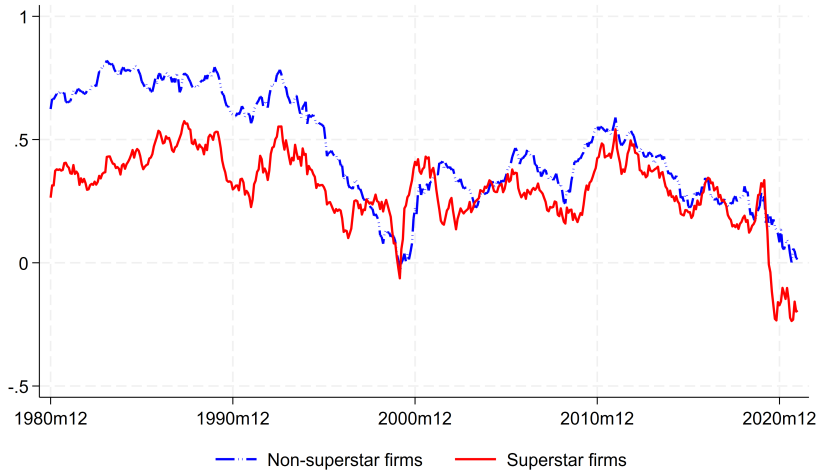

**Notes:** Panel A of this figure plots the sales-weighted average markup of large-cap and small-cap companies. We define large-cap and small-cap companies as those with market capitalizations above and below the NYSE median. Panel B plots the 20-year (backward) rolling average value premium (in percentage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

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

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



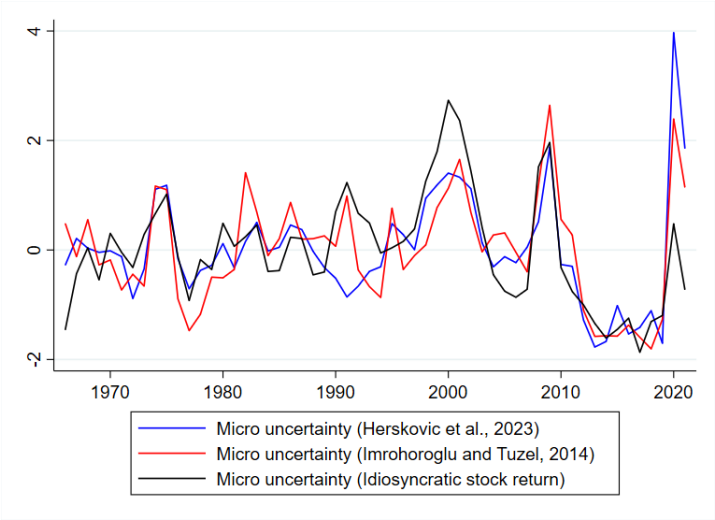

**Panel B: value premium among superstar and non-superstar firms**



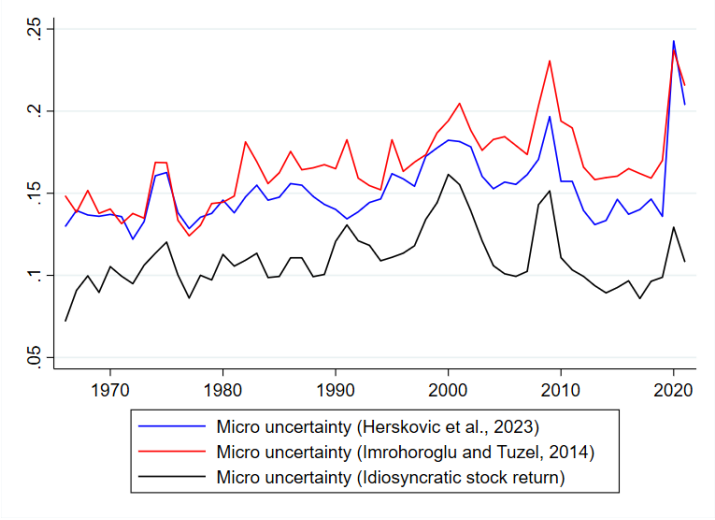

**Notes:** Panel A plots the sales-weighted average markup of superstar and non-superstar firms. We define superstar firms as the top 100 publicly traded non-finance firms in the US in terms of total sales each year. Panel B plots the 20-year (backward) rolling average value premium (in percentage per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

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

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




**Panel B: micro uncertainty (raw)**




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

**Table A.1: Alternative measures of value premium and sample periods**

**Panel A: post-1993 period value premium**

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

**Panel B: post-financial-crisis value premium**

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

**Panel C: excluding Covid-19 period**

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

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

**Table A.2: Excess returns of book-to-market and markup sorted portfolios**

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

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

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

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

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

**Table A.3: Average markup and value premium of different industries**

**Panel A: Change in industry-level markup**

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

**Panel B: Pre-2000 value premium**

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

**Panel C: Post-2000 value premium**

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

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

**Table A.4: Robustness check on the cross-sectional value premium post 2000**

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

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

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

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

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

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

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

**Table A.5: Robustness of markup trend under alternative measures**

**Panel A: measuring markup with cost elasticity**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Aggregate markup | | | Markup terciles | | |
| VARIABLES | EW | AW | SW | Low | Mid | High |
| Post-2000 | 0.30*** | 0.41*** | 0.21*** | 0.00 | 0.08*** | 0.70*** |
| | (12.71) | (12.56) | (10.11) | (1.07) | (6.75) | (12.94) |
| Constant | 1.49*** | 1.47*** | 1.38*** | 1.08*** | 1.28*** | 1.93*** |
| | (69.04) | (117.40) | (112.21) | (456.38) | (271.42) | (54.55) |
| Observations | 60 | 60 | 60 | 60 | 60 | 60 |
| Adjusted $R^2$ | 0.703 | 0.786 | 0.671 | 0.021 | 0.535 | 0.836 |

**Panel B: measuring markup with SG&A expense**

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

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

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

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

**Table A.6: Value premium post 2000, exclude micro-cap or superstars**

**Panel A: exclude micro-cap stocks**

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

**Panel B: exclude superstar stocks**

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

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

**Table A.7: Markup of superstar and non-superstar firms**

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

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

**Panel B: average markup of markup-sorted terciles**

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

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

**Table A.8: Cross-sectional correlation between markup and stock characteristics**

| | Markup | Size | BM | ROA | R&D | Int. K | Know. K | Org. K |
|---|---|---|---|---|---|---|---|---|
| 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 |

This table reports the cross-sectional correlation between markup and various stock characteristics. All variables are measured on an annual basis and de-meaned each year to remove time effects. Markup is sales divided by the cost of goods sold. Size is the log of market cap. BM is book-to-market ratio. ROA is net income before 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.

**Table A.9: Value premium and alternative characteristics**

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

This table reports the value premium in different characteristic sorted portfolios in pre-2000 and post-2000 period. In each panel, we double-sort stocks based on book-to-market and a stock characteristic. Value premium is the difference in return between stocks in the top bm quintile and stocks in the bottom bm quintile within each characteristic tercile. Columns 1 to 4 report pre-2000 period result, which is from 1963m7 to 2001m6, and columns 5 to 8 report post-2000 period, which is from 2001m7 to 2021m12. ROA is net income before 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. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table A.10: Change in markup, excluding new firms**

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

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

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

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

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

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

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