A Unified Explanation for the Decline of the Value Premium and the Rise of the Markup

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Abstract

We provide a unified explanation for two significant trends over recent decades: the decline of the value premium and the rise of the markup. We show that these trends are primarily driven by high-markup firms, while both the value premium and the markup remain stable among firms with low markups. We develop a dynamic monopolistic competitive equilibrium model featuring a stochastic technology frontier and heterogeneity in firms' technology adoption decisions to explain these findings. We show that both the cross-time increase in the efficiency of the aggregate technology frontier and cross-firm heterogeneities in adoption benefits and demand elasticity are crucial to generate the observed trends in markups and the value premium, as well as the cross-sectional difference in these trends.

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

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1 Introduction

Recent studies have documented a decline in the value premium and a rise in markups over last decades (see, for example, Fama and French (2021); De Loecker, Eeckhout, and Unger (2020)). We provide a unified framework to understand both trends. Empirically we find that the decline in the value premium is primarily driven by firms with high markups. These firms have also experienced significant increases in their markups over recent decades, leading to a rise in the aggregate markup. In contrast, firms with low markups have seen no change in either their value premium or markup levels. We propose a dynamic monopolistic competitive equilibrium model that incorporates a stochastic technological frontier and costly endogenous technology adoptions. Our model demonstrates that improvements in the efficiency of the aggregate technological frontier and heterogeneities in firms' technology adoption decisions are key to explaining the simultaneous decline in the value premium and the increase in markups, and the cross-sectional variations in these trends.

We start off by documenting a decline of the value premium in the past few decades. Consistent with Fama and French (2021), the spread between high and low book-to-market quintile portfolios falls significantly from 5.7% in 1963-2001 to -0.4% in 2001-2021. Similarly, the CAPM alpha of the value premium also decreases substantially from 6.6% to -3.6%. The decline of the value premium is also robust to alternative time cutoff and other measures of the value investing, for instance, the HML factor exhibits a similar decline.

We demonstrate that the decline in the value premium is closely linked to the rise in firms' markups. Specifically, we find that this decline is predominantly driven by firms with high markups, where the value premium drops from 9.4% in 1963-2001 to -3% in 2001-2021. In contrast, it remains sizable in low markup firms, fluctuating from 5.3% in 1963-2001 to 7.3% in 2001-2021. Notably, the same high markup firms also exhibit significant increases in their markups over this period from 2.19 in 1963-2001 to 3.33 in 2001-2021, whereas those of low markup firms remain unchanged at around 1.2. These patterns collectively contribute to an overall increase in the aggregate markup from 1.66 in 1963-2001 to 2.13 in 2001-2021.

These findings shed lights on De Loecker, Eeckhout, and Unger (2020), who highlight the importance of understanding rises in aggregate markup to understand changes in market structure.

To understand the economic forces driving the empirical findings, we develop a dynamic monopolistic competitive equilibrium model with two key features: (i) an aggregate technology frontier fluctuates over time, capturing changes in advanced technologies, and (ii) costly technology adoption by firms. In the model, firms can upgrade their technology by adopting the latest technology, albeit at a fixed cost. The advantage of adopting new technology is that it increases production efficiency by reducing operating costs. This efficiency improvement captures the fact that new technologies-such as ICT, cloud storage and computing, automation, AI, etc., -enable firms to expand into multiple product lines or markets, thereby lowering the marginal cost in production as the new technologies are non-rival and scalable (Aghion, Bergeaud, Boppart, Klenow, and Li (2023), Hsieh and Rossi-Hansberg (2023)). Furthermore, a lower operating cost also leads to lower exposures to the aggregate technology frontier shocks.

Our model also incorporates several types of heterogeneity. First, the efficiency of new technologies varies across time periods, capturing significant advancements in aggregate technology since the late 1990s. Second, benefits from technology adoption captured by the marginal production costs vary across different groups of firms. Third, market power (demand elasticity) also varies across different groups of firms. Lastly, there is within-group heterogeneity in firm-specific productivity which creates dispersion in firm-level risk. We identify these heterogeneities through using both asset pricing and quantity moments across firms and over time.

We first calibrate our model to capture the pre-2000 economy and show that it produces a value premium close to the data. In the model, value firms are more exposed to the frontier shock than growth firms, because they lag behind the technology frontier but cannot catch up the latest technology due to the adoption cost. As a result, their cashflows are more affected by the changes in the aggregate technology frontier and hence are riskier. Additionally, the model also generates significant CAPM alphas, consistent with empirical evidence that the CAPM fails to account for the value premium. Intuitively, in the model the cross-sectional risk dispersion is driven primarily by aggregate technology frontier shocks, whereas the market return is driven more by aggregate 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 heterogeneities across-time and across-firms. Regarding aggregate technology, we assume that the efficiency of the technology frontier increases significantly, capturing advancements in information and communication technologies, artificial intelligence, machine learning, and smarter devices, which impact all firms. Furthermore, the benefit from adopting these technologies varies across firms, specifically firms with lower marginal production costs have higher adoption benefits. Additionally, we assume that firms with higher adoption benefits also face less elastic demand, namely firms with lower marginal cost of production possess higher market power. We show that firms with higher technology adoption benefit choose to adopt the frontier technology, additionally these firms also have significant increase in their markups as their marginal operating costs decrease more substantially and that they have higher market power. This drives the aggregate markup to rise. Due to the decrease in the operating costs for all high markup firms, the dispersion in exposures to aggregate technology frontier shocks shrinks, leading to the decline in the value premium. Contrary to firms that adopt new technologies, firms with lower benefits from technology adoption do not keep pace with the technology frontier and continue to operate with outdated technology, incurring high operating costs. These non-adopting firms also maintain low markups due to their high marginal costs of production and low market power. Consequently, the dispersion in exposure to aggregate frontier shocks remains significant among these low markup firms, as the effect of operating costs is still pronounced. This results in a sizable value premium persisting within this group.

We conduct several counterfactual analyses to understand the model mechanisms. We show that both the cross-time and cross-firm heterogeneities are crucial for generating observed trends in markups and the value premium, as well as the cross-sectional differences in these trends. First, we reduce the increase in the efficiency of the aggregate technology frontier in the post-2000 economy by 50% compared to the baseline calibration. We see that the markup of high markup firms becomes counterfactually too small while the value premium rises; on the other hand, the low markup firms' value premium rises and markups fall compared to the baseline. Second, we study the impact of cross-firm heterogeneities by turning them off one at a time. Shutting down heterogeneity in adoption benefits results in an 80% reduction in the markup difference and a 35% decrease in the value premium difference between low and high markup firms relative to the baseline. Moreover, removing heterogeneity in demand elasticity reduces these differences by 20% and 25%, respectively. Taken together, these findings highlight that increases in the efficiency of the aggregate frontier and differences in adoption benefits across firms 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, while heterogeneity in firms' market power also plays a significant quantitative role.

Lastly, in the model, firms maximize their market value by considering expectations about their own and their competitors' states, e.g., market structure, which influence product market competition and the efficacy of technology adoptions. We focus our analysis on the Markov perfect equilibrium (MPE) as outlined by Ericson and Pakes (1995). To circumvent the significant computational challenges associated with the MPE, especially when dealing with a large number of firms, we adopt the oblivious equilibrium concept proposed by Weintraub, Benkard, and Van Roy (2008). In the oblivious equilibrium, firms base their decisions on a long-term average belief about the industry structure instead of competitors' states. This approach closely approximates the MPE when the number of firms in the industry is large.

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

The paper also closely relates to the recent studies on the decline of the value premium. Fama and French (2021) document a substantial decline in the value premium over the last few decades. Several studies, such as those by Park et al. (2019), Arnott, Harvey, Kalesnik, and Linnainmaa (2021), Eisfeldt, Kim, and Papanikolaou (2022), and Gulen, Li, Peters, and Zekhnini (2021), suggest that the decline can be attributed to traditional book-to-market ratios non including intangible assets. These studies show that incorporating intangible assets into the book-to-market ratios significantly improves the performance of value investing strategies, but they are salient about the decline of value premium. Gonçalves and Leonard (2023) show the decline of value premium happened because book equity is no longer a good proxy for fundamental equity. We differ from these findings by showing that the decline in the value premium is primarily driven by firms with high markups. We quantify this effect in an equilibrium model with technology adoptions, thus providing a comprehensive analysis of the underlying mechanisms.

Our paper also contributes to the literature examining the link between technological changes, the macroeconomy, and financial markets. Papanikolaou (2011), Kogan and Papanikolaou (2014), and Garlappi and Song (2017) have explored the asset pricing implications of investment-specific technological shocks. We differ in that we follow the extensive body of literature that investigates the impacts of shifts in the aggregate technology frontier-examples include works by Parente and Prescott (1994), Greenwood and Yorukoglu (1997), Cooper, Haltiwanger, and Power (1999), and more recent analyses by Lin, Palazzo, and Yang (2020). Our model allows for endogenous technology adoption and investment decisions, and it specifically links the decline of the value premium to the rise of the markup. Different from the negative price of the IST shocks, the positive price of technology frontier risk is supported by the evidence in Baron and Schmidt (2017), who show that consumption rises after an aggregate shock to the technology frontier, and in Jovanovic and Rousseau (2005), who show that consumption rises during the two major eras of technology frontier growth, the Electrification era and the IT era, and in Lin, Palazzo, and Yang (2020) who estimate the price of risk of technology frontier shocks and obtain a positive and significant value.

Furthermore, our paper contributes to the growing body of research exploring how market power influences macroeconomic dynamics and asset prices. Recent studies have focused on the interactions between competition, asset pricing, and industry dynamics, e.g, Carlson, Dockner, Fisher, and Giammarino (2014), Bustamante (2015), Bustamante and Donangelo (2017), Corhay (2017), Chen et al. (2019), Corhay, Kung, and Schmid (2020), Dou and Ji (2021), Dou, Ji, and Wu (2021, 2022) etc. Our paper differ from these studies in two notable ways. Firstly, we establish a novel link between markup trends and cross-sectional returns in our model, addressing empirical observations not yet explored in prior literature. Secondly, we focus on a monopolistic competitive equilibrium model as the industry structure to explore the implications of firms' decisions to adopt frontier technologies on asset prices and markups, while the existing literature mostly explores oligopoly models.

Our paper also contributes to the broad literature on production-based asset pricing which explores the driving forces of risk and returns through firms' decisions, including Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Belo, Lin, and Bazdresch (2014), Favilukis and Lin (2016), etc. Kogan and Papanikolaou (2012) offer a comprehensive review of the developments of this literature. Our study extends this literature by investigating the economic mechanisms that contribute to the time trends in the value premium and the macroeconomy.

Lastly, our model relates to the recent IO literature on industry structure dynamics within strategic competition contexts, particularly those involving dynamic games. Foundational studies by Maskin and Tirole (1988a,b) and Ericson and Pakes (1995) introduce the concept of Markov Perfect Equilibrium (MPE) and explore the implications for equilibrium conditions in industry dynamic model. Weintraub, Benkard, and Van Roy (2008) work out an MPE model where firms only keep track of their own states and the industry states to capture strategic competition. We build on these works and explore asset pricing implications of an MPE model in a monopolistic competitive industry with endogenous technology adoption.

The paper proceeds as follows. Section 2 shows the empirical links between the trend of markups and the value premium. Section 3 presents the model. Section 4 presents the quantitative results. Section 5 inspects the mechanism. Finally, Section 6 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 first document the decline of the value premium, then rise of the markup and last the robustness checks.

2.1 Data

We collect data from standard sources. Stock return and market capitalization are from CRSP. Accounting information is from Compustat. We download factor returns and return on book-to-market (BM) sorted portfolios from Ken French's website. Our sample period is from July 1963 to June 2021.

2.2 The decline of the value premium

This section documents the decline of value premium after the turn of the century. We use several measures to demonstrate this decline in Table 1, including the average return and the CAPM alpha of the HML factor and various value-minus-growth long-short portfolios. The data for Table 1 are from Ken French's website.

Table 1 Panel A shows that the average excess return and the CAPM alpha of the HML factor, value-minus-growth quintile portfolio, HML factor in large cap stocks, and HML factor in small cap stocks from July 1963 to June 2001. During these 38 years, value stocks consistently outperform growth stocks. For example, the average HML factor return is 0.45% per month with a t-statistic of 3.26. The average return of the value-minus-growth quintile portfolio is 0.48% per month with a t-statistic of 2.91. Similarly, HML factors constructed from large cap and small cap stocks both have statistically positive returns during this sample period. The CAPM alpha of these returns are higher and more statistically significant. For example, the CAPM alphas of the HML factor and the value-minus-growth quintile portfolio are 0.58% and 0.55% per month, respectively, with t-statistics being 4.7 and 3.44. The CAPM alpha of large-cap HML factor is 0.42% per month (t-statistic: 3.04) and small-cap HML factor is 0.74% per month (t-statistic: 5.49).

Table 1 Panel B shows the performance of these value-minus-growth portfolios from July 2001 to June 2021. During the recent 20 years, value premium has disappeared both in terms of average excess return and CAPM alpha. For example, the average returns of the HML factor and the value-minus-growth quintile portfolio are negative, at -0.07% and -0.04% per month, respectively. Their CAPM alphas are more negative, at -0.16% and -0.3% per month, during this period. The HML factor among large cap stocks underperforms the most. Its average return and CAPM alpha are -0.21% and -0.43%, respectively. Even among small cap stocks, where value premium is historically the strongest, the HML factor only returns 0.07%

per month in excess return and 0.12% per month in CAPM alpha and neither is statistically significant as shown in columns 7 and 8 of Panel B.

Panel C of Table 1 reports the difference in return between the two sample periods by estimating an OLS regression with a dummy variable. The dummy variable indicates whether an observation is after June 2001. The coefficients on the dummy variable in columns 1, 3, 5, and 7 are the difference in average returns between the two sample periods. In columns 2, 4, 6, and 8, we control the market factor in the regression, so the coefficients on the dummy variables represent the difference in CAPM alpha.

In all eight columns of Panel C, the coefficients on the dummy variable are significantly negative with t-statistics ranging from -1.65 to -2.25. The magnitudes of these coefficients are economically large, ranging from -0.44% to -0.54% per month. Notably, the HML factors among both large cap and small cap stocks experience significant decline with similar magnitudes. This suggests that the decline might not be driven by arbitrageurs or other liquidity related reasons. Overall, Table 1 indicates that there is a large and significant decline in value premium in the recent years. Figure 1 plots the 20-year rolling average return and CAPM alpha of the top-minus-bottom BM quintile return. Consistent with Table 1, the figure shows a clear declining trend starting from approximately 2001. The 20-year rolling average return and CAPM alpha of the value spread are positive until the most recent years. In the past two decades, we have witnessed the worst performance of value stocks relative to growth stocks.

In the Appendix, we conduct several robustness checks for the results in this table. For example, we vary the cut-off date that separates the two sub-sample periods. We also exclude the data in 2020 and 2021 to remove the influence of the Covid-19 pandemic. The results of robustness checks are similar to Table 1.

2.3 The rise of the markup

Another important macroeconomic trend as documented by De Loecker, Eeckhout, and Unger (2020) is the rapid rise of the aggregate markup. Motivated by De Loecker, Eeckhout, and Unger (2020), we measure the markup of a firm as the ratio between its revenue and cost of goods sold. Figure 2 shows the average markup in the economy from 1962 to 2020. It shows that the average markup was around 1.5 in the 60s and 70s, and started to rise since the 80s. The average markup has reached to 2.2. in 2020. Using alternative ways to average markup produces similar trends. In Table 2 Panel A, we test the difference in aggregate markup before and after June 2001. We can see that the economy wide average markup, whether cost-weighted, equal-weighted, or sales-weighted, is significantly higher after June 2001. Column 1 of Panel A shows that cost-weighted average markup is 1.41 before 2001 and 1.49 after 2001, a 5.7% increase between the two sample periods. Columns 2 and 3 show that increases in equally weighted and sales weighted average markups are even greater. Equally weighted markup increases by 0.47 and sales-weighted average markup increases by 0.29.

The markup of all firms do not rise up uniformly. We find that high-markup firms, i.e., firms with strong market power, are most responsible for the rise of the aggregate markup. Their markups increase much more rapidly than other firms. Table 2 Panel B shows this result. In this panel, we first sort all firms into three terciles based on their individual markup in the prior year. Then, we measure the average markup for each group of firms in each year. Panel B Column 1 shows that the average markup of the bottom markup tercile remains stable over the two periods. Column 2 shows that the average markup of firms in the mid-markup tercile increases by 0.11 from 1.42 before 2001 to 1.53 after 2001, which is an increase of 8%. Finally, Column 3 shows that the average markup of high-markup firms rises the most. It increases by 1.14 from 2.19 before 2001 to 3.33 after 2001, which is an increase of more than 50%. Figure 3 plots the time series of average markup in each group of firms from 1962 to 2020, which shows the similar picture.

As a robustness check, we sort industries based on the industry average markup and find similar results. Industries with higher markups before 2001 experience larger increase in their markups after 2001. This result is presented in the appendix.

2.4 The value premium decline and the markup rise

Is the decline of value premium related to the rise in markup? We provide supportive evidence to this question. This section presents the result of cross-sectional relationship between markup and value premium. We find that the decline of value premium is concentrated among firms with medium and high markups, while the value premium among firms with low markup remains the same. To demonstrate this result, we first sort firms into three terciles based on their individual markup, measured as revenue divided by cost of goods sold. Then, we independently sort firms into quintiles based on their book-to-market ratio. This double sort produces 15 different portfolios of stocks.

Table 3 reports the average return and CAPM alpha of portfolios from double sorting on firm-level markup and book-to-market ratio. Table 3 Panel A reports the average return of these 15 portfolios as well as various long-short portfolios from July 1963 to June 2001. In all three markup groups, high BM stocks (value stocks) outperform low BM stocks (growth stocks). The difference of their average returns are 0.44%, 0.79%, and 0.78% per month among low-markup, mid-markup, and high-markup firms, respectively. The difference in value premium between low-markup and high-markup firms is not significant in this early sample period.

Table 3 Panel B reports the corresponding average return from July 2001 to June 2021. In the later sample period, only among low-markup firms, value stocks have significantly higher average return than growth stocks. Low-markup value stocks outperform low-markup growth stocks by 0.61% per month (t-statistic: 2.04) in the past twenty years. In contrast, among mid-markup and high-markup industries, value stocks underperform growth stocks by 0.28% and 0.25% per month, respectively. Also in this later sample period, the value premium among high-markup firms is significantly lower than the value premium among low-markup firms. The difference between the two is -0.87% per month (t-stat: -2.65). Panel C and D of Table 3 reports the CAPM alpha of these portfolios in the two sample periods. The results are qualitatively the same. In the first sample period, the CAPM alphas of the value-minus-growth quintile are positive in all three markup groups, whereas in the second sample period, only among low markup firms, the CAPM alpha of the value-minus-growth quintile is positive. Similarly, the difference in the CAPM alpha of the value premium between low-markup and high-markup firms is significantly negative in the recent sample period.

We perform the same exercise by sorting firms based on their industry markup. Measuring markup at the industry level can potentially reduce measurement error. Specifically, we first sort SIC 4-digit industries into three groups based on the ratio between total industry sales and total industry cost of goods sold. Then, we pool firms in each industry group together and independently sort firms into quintiles based on their book-to-market ratio.

Table A.5 Panel A reports the average return of these 15 portfolios as well as high-minus-growth quintile from July 1963 to June 2001. In all three industry markup groups, high BM stocks (value stocks) outperform low BM stocks (growth stocks). The difference of their average returns are 0.59%, 0.68%, and 0.80% per month among low-markup, mid-markup, and high-markup industries, respectively. The difference in value premium between low-markup and high-markup industries is not significant in this early sample period. Table A.5 Panel B reports the corresponding average return from July 2001 to June 2021. In the later sample period, only within low-markup industries, value stocks have higher average return than growth stocks. Value stocks from low-markup industries outperform growth stocks from low-markup industries by 0.75% per month. In contrary, from mid-markup and high-markup industries, value stocks underperform growth stocks by 0.18% and 0.23% per month, respectively. Also in this sample period, the value premium from high-markup industries is significantly lower than the value premium from low-markup industries. The difference between the two is -0.98% per month (t-stat: -2.58). Panels C and D of Table A.5 reports the CAPM alpha of these portfolios. The results are similar to Panels A and B. Before June 2001, the CAPM alpha of the value-minus-growth long-short portfolios are all significantly positive in low-, mid-, and high-markup industries. They are, respectively, 0.72%, 0.81%, and 0.79% per month (with t-statistics at 3.32, 3.72, and 3.54). After June 2001, the CAPM alpha of the value-minus-growth portfolios are negative in mid-, and high-markup industries, while it remains positive in low-markup industries.

Table 4 estimates the change in the return and CAPM alpha of value-minus-growth quintile portfolio among low-, mid-, and high-markup firms or industries during the two sample periods. Panel A sorts stocks based on firm-level markup and reports the value premium change in each markup tercile. We estimate value premium change in OLS regressions with a dummy variable that indicates if a month is after June 2001. The coefficient on the dummy variable in column 1 is 0.18, which means that average value premium in this group of firms actually increases by 0.18% per month after 2001, although this increase is not statistically significant. Columns 2 and 3 show that the value premium among mid- and high-markup firms decline by more than 1% per month. Column 4 compares the value premium among low- and high-markup firms and shows that value premium declines significantly more among high-markup firms. Columns 5 to 8 report change in the CAPM alpha of the value premium and results are largely the same as columns 1 to 4. Panel B sorts stocks based on industry-level markup. We have similar findings. There is no statistically significant change in value premium among firms in low-markup industries, but among firms in mid- and high-markup industries, value premium significantly decline after 2001.

This section shows that the decline of value premium depends on the firm's markup. The value premium has significantly declined among mid- and high-markup firms or industries, while it remains relatively stable among low markup firms or industries.

2.5 Robustness checks and additional analysis

Cutoff dates Our first robustness check is whether the decline of value premium depends on the choice of cut-off date. We select two other cut-off dates. One is 1993 June and the other is 2007 June. We report the change in value premium between the two sample periods in Table A.1. Panel A of Table A.1 splits the sample by the June 1993 cut-off date. We can see that the decline in value premium is significant in five of the eight columns. The magnitude of the decline is economically large, ranging from -0.24% to -0.53% per month. This is similar to the result in Table 1. Similarly, when we choose June 2007 as the cut-off date, the decline in value premium between the past and recent sample periods is more significant. The magnitude of the decline ranges from -0.71% to -0.85% and all eight columns are statistically significant at the five percent level. In Panel C, we show that the decline of the value premium is also robust to excluding the Covid-19 pandemic period.

Intra-industry variation The literature has shown that the value premium is largely an intra-industry phenomenon (Cohen and Polk (1998); Novy-Marx (2011)). We verify that intra-industry value premium also has declined in Table A.2. we measure intra-industry value premium by first measure value premium (the difference in return between stocks in the top and bottom book-to-market quintile) within in each Fama-French 30 industry and take average across industries. We use the total industry market cap as weights to average each industry's value premium. Columns 1 and 4 of Table A.2 shows that the intra-industry value premium before 2001m6 is highly significant, both in terms of average return and CAPM alpha. Columns 2 and 5 shows that after 2001m6, intra-industry value premium is insignificantly different from 0. Columns 3 and 6 estimate the difference in value premium between the two sub-periods and show that intra-industry value premium has significantly declined by about half a percentage point per month.

Our next robustness check evaluates the change in markup among low-, mid-, and high-markup industries. Specifically, we computer the average markup of Fama-French 30 industries (excluding utilities and financials) and compare the change in markup before and after

2001. Table A.3 shows the average markup of each industry. Industries such as healthcare, personal and business services, and printing and publishing have had the biggest increase in markup. Industries such as electrical equipment, coal, and shipping have seen a decline in markup. We run OLS regressions that regress change in markup on the pre-2001 average markup of each industry in Table A.4. The coefficients on the pre-2001 average markup are significantly positive, which means industries with higher markup before 2001 experience greater increase in markup both in level and in percentage after 2001.

Alternative measures of markups Another robustness check is whether our cross-sectional result on the decline of value premium is robust to alternative measures of markup. We also measure markup based on industry-level markup, based on the measure from De Loecker, Eeckhout, and Unger (2020), and based on operating leverage. The results are presented in Tables A.5, A.6, and A.7. The results are similar to our main finding in Table 3. High markup firms (or firms with low operating leverage) experience greater decline in value premium after 2001.

Size effect We also check whether our cross-sectional result on the decline of value premium is influenced by micro-cap stocks. We drop micro-cap stocks from our sample and estimate the change in value premium in different markup terciles. The results are reported in Table A.8, where we sort stocks based on firm-level markups, and in Table A.9, where we sort stocks based on industry-level markups. In both tables, we see that value premium remains positive among low markup firms or industries and the change in value premium in this group is not statistically different from zero. On the other hand, in mid- and high-markup groups, value premium becomes negative in the past twenty years and the change in value premium is statistically significantly negative. This indicates that our results are robust to excluding micro-cap stocks.

Intangible assets We examine the relationship between value premium and intangible assets. First, we do not find any relationship between the decline of value premium and the amount of intangible capital a firm has. Over the past twenty years, the value premium becomes insignificant among firms with either high or low amount of intangible capital. To show this, we sort all firms into three groups based on various proxies of intangible assets, such as R&D expense, knowledge capital, and organizational capital. We find that value premium is insignificant and barely positive in any group of firms. Difference in value premium between firms with low and high amount of intangible assets is not significant either. Table A.10 presents the result of this exercise. In the second test, we add the amount of intangible asset to a firm's book value and then compute intangible-asset-augmented-book-to-market ratio. This measures can potentially reduce the mismeasurement problem in book value given that intangible assets are not capitalized. We use the new ratio to compute value premium and find that the intangible-asset-augmented value premium also has declined significantly after 2001. As shown in Table A.11, we construct different measures of intangible-asset-augmented value premium. In columns 1 to 3, we add knowledge capital, organizational capital, and all intangible capital to book-equity and then compute intangible augmented book-to-market.[1] We sort firms based on this measure into quintiles and report the CAPM alpha of high-minus-low returns. In column 4, we use the intangible HML factor constructed by Eisfeldt, Kim, and Papanikolaou (2022). As shown in the table, before 2001m6, all four types of value premia have significantly positive alpha. After 2001m6, none of these is significant. The decline in alpha is large and mostly significiant. This table shows that the mismeasurement problem may not be the sole reason of the decline of value premium.

3 Model

In this section, we present a dynamic monopolistic competitive equilibrium model featuring a stochastic technology frontier and costly technology adoption to understand the economic mechanism underlying the empirical findings. Moreover, our model allows for strategic competition and incorporates several sources of heterogeneities: the first is the

[1] These measures are obtained from Peters and Taylor dataset on WRDS.

cross-time difference in the efficiency of the aggregate technology frontier, the second is differences in the benefit of frontier technology adoption and demand elasticity (market power) across different groups of firms, and the last is firm-specific productivity.

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, et al 2020; Hsieh and Rossi-Hansberg, 2020). Cross-group heterogeneity reflects the variation in benefits that firms derive from adopting new technologies, which can be attributed to the match between new technology and organizational structures. Firm-specific productivity generates firm-level heterogeneity. We identify both cross-time and cross-firm heterogeneities by using both asset pricing and quantity moments across firms and over time.

3.1 Demand

All firms 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:

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

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 industry aggregate output and price index.[2] The parameter $\xi\left(\mathcal{F},\mathcal{T}\right)$ controls the elasticity of substitution between different products with $(\mathcal{F},\mathcal{T})$ denoting that ξ is heterogeneous across firms and over time. This demand function is consistent with Dixit and Stiglitz (1977) who characterize the structure of the standard monopolistic competition model, and is also used in the literature, e.g., Corhay, Kung, and Schmid (2020), Aw, Roberts, and Xu (2011), Yang and Xu (2022) among others.

[2]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.

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

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

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

$$y_{j,t} = \frac{P_t^{\xi(\mathcal{F},\mathcal{T})-\eta}}{p_{j,t}^{\xi(\mathcal{F},\mathcal{T})}}, \tag{3}$$

where the demand elasticity of substitution across products within an industry is higher the elasticity of substitution across industries $\xi\left(\mathcal{F},\mathcal{T}\right) > \eta$ (Corhay, Kung, and Schmid (2020)).

3.2 Production technology

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

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

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

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

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

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

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

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

Physical capital accumulation is given by

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

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

Following Abel and Eberly (1994), we assume that capital investment entails adjustment costs, denoted as $g_{j,t}$, with the sale price of capital being lower than the purchase price. We normalize the purchase price to 1 and denote the sale value of capital as $0 \leq c_k \leq 1$. The adjustment costs are given by:

$$g_{j,t} = i_{j,t} 1_{\{i_{j,t}>0\}} + c_k i_{j,t} 1_{\{i_{j,t}<0\}}$$

3.3 Technology frontier and technology adoptions

Motivated by Parente and Prescott (1994), Parente (1995) and Lin, Palazzo, and Yang (2020), we assume that the stock of general and scientific technology of the entire economy, denoted by S_t, evolves stochastically This stock of technology encompasses new production technologies that generate productivity gains. These include information, communication, and telecommunication (ICT) technologies, cloud storage and computing, automation, and innovative management practices that enhance firm efficiency. We assume that the stochastic technology frontier S_{t+1} follows the process below:

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

in which $s_{t+1} = \log(S_{t+1})$, ε^s_{t+1} is an i.i.d. standard normal shock that is independent of all the other shocks in the economy, and ρ_s, and σ_s are the autocorrelation and conditional volatility of the technology frontier shock, respectively. $\bar{s}(\mathcal{T})$ is the long-run mean of the technology frontier and $\mathcal{T}$ denotes the time-heterogeneity of the long-run efficiency which captures the pre-2000 technology era and the post-2000 new IT technology era.

Given the aggregate technology frontier and the aggregate/idiosyncratic productivities, firms can advance their technology level by choosing to adopt the latest advancements. This choice determines their firm-specific technology capital $n_{j,t}$. Firms' technology capital $n_{j,t}$ directly increases production efficiency by reducing operating costs.

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

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

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

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

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

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

The benefit of adopting the frontier technology is that firms are more efficient with lower operating costs, which is given by $\frac{f_o(\mathcal{F},\mathcal{T})}{S_t}k_{j,t}$ with $f_o(\mathcal{F},\mathcal{T}) > 0$, where $\mathcal{F}$ denotes the heterogeneity in production cost across groups.This implies that adoption costs not only fluctuate over time but also vary across firms. For firms that choose not to adopt, they keep operating with the old technology that depreciates over time and the operating cost is given $\frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_n)n_{j,t-1}}k_{j,t}$. Hence the operating costs $oc_{j,t}$ is given by

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

This assumption highlights several ways in which new technologies can enhance firm efficiency by reducing 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)). As inDe 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)). These intangible inputs, typically customized for the firm that deploys them, are rarely patented, which limits positive spillovers to competitors (e.g., Bessen 2020; Aghion et al. 2022). As in De Ridder (2024), the new technologies, typically customized for the firm that deploys them, are rarely patented, which limits positive spillovers to competitors so that they are distinct from R&D.

To sum up, the total costs $tc_{j,t}$ for firms are

$$tc_{j,t} = ac_{j,t} + oc_{j,t} = \begin{cases} \frac{f_o(\mathcal{F},\mathcal{T})}{S_t}k_{j,t} + f_a, & \text{if } \phi_{j,t} = 1 \\ \frac{f_o(\mathcal{F},\mathcal{T})k_{j,t}}{(1-\delta_n)n_{j,t-1}}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{14}$$

3.4 Firms' maximization problem

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

$$d_{j,t} = rev_{j,t} - g_{j,t} - h_{j,t} - tc_{j,t}. \tag{15}$$

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

$$M_{t,t+1} = \exp\left(-r_f\right) \frac{\exp\left(-\gamma_x \triangle x_{t+1} - \gamma_s \triangle s_{t+1}\right)}{E_t\left[\exp\left(-\gamma_x \triangle x_{t+1} - \gamma_s \triangle s_{t+1}\right)\right]} \tag{16}$$

where r_f is the (log) risk-free rate, $\gamma_x > 0$ and $\gamma_s > 0$ are the loadings of the stochastic discount factor on the two aggregate shocks. The sign of the risk factor loading parameters (γ_a and γ_s) is positive, consistent with the evidence reported in the empirical section (we also perform comparative statics to these parameters to understand its importance on the model results). The risk-free rate is set to be constant. This allows us to focus on risk premia as the main driver of the results in the model as well as to avoid parameter proliferation.

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

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

$$v_{j,t}\left(\Theta_t\right) = \max_{i_{j,t}, \phi_{j,t}} : \left\{d_{j,t} + E_t\left[M_{t,t+1} v_{j,t+1}\left(\Theta_{t+1}\right)\right]\right\}, \tag{17}$$

subject to the capital accumulation equation (8) and the flow of funds constraint (15) for all dates t given a law of motion for the joint distribution of idiosyncratic productivity, capital and technology capital

$$\chi_{t+1} = \Gamma\left(X_t, S_t, \chi_t\right) \tag{18}$$

3.5 Equilibrium

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

3.5.1 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 (1988) and Ericson and Pakes (1995), we focus on the Markov Perfect Equilibrium. In this framework, the optimal strategies of firms depend on the current states that affect their payoff functions. In the model, firms' strategies include the physical investment strategy $i_{j,t}\left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$, and the technology capital strategy $n_{j,t}\left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$. 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 $n_{j,t}\left(k_{j,t}, n_{j,t-1}, z_{j,t}; X_t, S_t, \chi_t\right)$ given the current individual states, aggregate states, and the perceived transitional kernel of the industry state χ_t.
- These perceptions align with the behaviors of each firm's competitors.
- Industry aggregation holds with $Q_t = P_t^{-\eta}$ and $Q_t = \int_j y_{j,t} dj$.

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

Weintraub, Benkard, and Van Roy (2008) demonstrate that the industry state forms an aperiodic Markov chain when firms' equilibrium strategies depend solely on the long-run industry state. They show that in non-concentrated markets, individual firms gain no advantage from unilaterally deviating to an optimal yet non-obvious strategy by monitoring the true industry state as the long-run average industry state. They show that obvious equilibrium closely approximates the Markov perfect equilibrium where industries have a large number of firms. Our approximation approach assumes that the average industry state is captured by the aggregate capital $K_t = \int_j k_{j,t} dj$ and approximate the law of motion of K_t and P_t. Appendix B details the numerical procedure of solving the Markov perfect equilibrium.

3.5.2 Equilibrium risk and return

In the model, risk and expected stock returns are determined endogenously along with the firm's optimal investment and financing decisions. To make the link explicit, we can evaluate the value function in equation (17) at the optimum and obtain

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

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

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 $r^s_{j,t+1} = v_{j,t+1}(\Theta_{t+1}) / [v_{j,t}(\Theta_t) - d_{j,t}]$. Substituting the stochastic discount from equation (16) into equation (20), and some algebra yields the following equilibrium asset pricing equation:

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

in which $r^e_{j,t+1} = r^s_{j,t+1} - R_f$ is the stock excess return, $\lambda_a = \gamma_a Var\left(\triangle a_{t+1}\right)$ and $\lambda_s = \gamma_s Var\left(\triangle s_{t+1}\right)$ are the price of risk of the aggregate productivity shock and aggregate operation cost shock, respectively, and $\beta^{j,a} = \frac{Cov\left(r^e_{j,t+1}, \triangle a_{t+1}\right)}{Var(\triangle a_{t+1})}$ and $\beta^{j,s} = \frac{Cov\left(r^s_{j,t+1}, \triangle s_{t+1}\right)}{Var(\triangle s_{t+1})}$ 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 (γ_a and γ_s) in the stochastic discount factor in equation (16). The pre-specified sign of the loadings imply a positive price of risk of both the aggregate productivity shock and the frontier shock. Thus, all else equal, assets with returns that have a high positive covariance with the aggregate productivity shock or the frontier shock are risky and offer high average returns in equilibrium.

3.6 Markups

Following De Loecker, Eeckhout, and Unger (2020), we define the markup as the price-marginal cost ratio $\mu_{j,t} = \frac{p_{j,t}}{\frac{\partial\left(oc_{j,t}\right)}{\partial y_{j,t}}}$. From equations (4) and (13), we can rewrite the operating costs as a linear function of firm's output $y_{j,t}$:

$$oc_{j,t} = \begin{cases} \frac{f_o(\mathcal{F},\mathcal{T})}{S_t X_t z_{j,t}} y_{j,t}, & \text{if } \phi_{j,t} = 1 \\ \frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_n) n_{j,t-1} X_t z_{j,t}} y_{j,t}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{22}$$

It results in $\mu_{j,t} = \frac{p_{j,t}}{\frac{\partial\left(oc_{j,t}\right)}{\partial y_{j,t}}} = \frac{p_{j,t} y_{j,t}}{oc_{j,t}}$, which implies that the markup is the share of input expenses as a proportion of total firm's revenues, consistent with De Loecker, Eeckhout, and Unger (2020) and the empirical measure for markup in the data.[3] From equation (3), we find

$$\mu_{j,t} = \begin{cases} (z_{j,t} X_t)^{1-\frac{1}{\xi(\mathcal{F},\mathcal{T})}} P_t^{1-\frac{\eta}{\xi(\mathcal{F},\mathcal{T})}} k_{j,t}^{-\frac{1}{\xi(\mathcal{F},\mathcal{T})}} \frac{S_t}{f_o(\mathcal{F},\mathcal{T})}, & \text{if } \phi_{j,t} = 1 \\ (z_{j,t} X_t)^{1-\frac{1}{\xi(\mathcal{F},\mathcal{T})}} P_t^{1-\frac{\eta}{\xi(\mathcal{F},\mathcal{T})}} k_{j,t}^{-\frac{1}{\xi(\mathcal{F},\mathcal{T})}} \frac{(1-\delta_n) n_{j,t-1}}{f_o(\mathcal{F},\mathcal{T})}, & \text{if } \phi_{j,t} = 0 \end{cases}. \tag{23}$$

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

4 Model results

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

4.1 Calibration

The model is solved at a quarterly frequency. Because all the firm-level accounting variables in the data are only available at an annual frequency, we time-aggregate the simulated accounting data to make the model-implied moments comparable with those in the data. Table 5 reports the parameter values used in the baseline calibration of the model, which are either based on the previous studies, or whenever possible, by matching the selected

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

moments in the data reported in Table 6. To generate the model's implied moments, we simulate 3, 600 firms for 1, 000 quarterly periods. We drop the first 400 quarters to neutralize the impact of the initial condition. The remaining 600 quarters of simulated data are treated as those from the economy's stationary distribution. We then simulate 200 artificial samples and report the cross-sample average results as model moments. Because we do not explicitly target the cross section of return spreads (and abnormal returns) in the baseline calibration, we use these moments to evaluate the model in Section 3.

Firm's technology: common parameters. We set the firm elasticity of demand curve $\xi = 5$ such that the return to scale of production function is 0.8, close to estimates in Burnside, Eichenbaum, and Rebelo (1995) and the value used in Khan and Thomas (2008). Additionally, we set the industry demand elasticity $\eta = 4$ and the capital depreciation rate δ_K is set to be 4% per quarter as in Bloom (2009). There is no readily available esimate for the depreciation of technology capital δ_n in the data, we set it to 7.5% (30% annually) within the range of empirical estimates of the depreciation rate for intangible capital in the literature. Following Cooper (2008) and Gomes and Schmid (2012), we set the capital adjustment cost parameter $c_k = 0$ to capture the irreversibility constraint on capital investment.

Stochastic processes. In the model, the aggregate productivity shock is essentially a profitability shock. We set the persistence of the aggregate productivity shock to be $\rho_x = 0.985$ and the conditional volatility to be $\sigma_x = 0.055$ to match the volatility of aggregate profits as in Belo, Lin, and Bazdresch (2014). In the data, we measure aggregate profits using data from the National Income and Product Accounts (NIPA). Given the volatility of the aggregate productivity shock, we set the persistence of the aggregate technology frontier shock to be $\rho_s = 0.86$ and the conditional volatility to be $\sigma_s = 0.07$ to match aggregate stock market volatility.

To calibrate the persistence and conditional volatility of the firm-specific productivity shock, we set $\rho_z = 0.94$ and $\sigma_z = 0.2$. The long-run average level of firm-specific productivity, $\bar{z}$, is a scaling variable. We set $\bar{z} = -0.3$, which implies that the average long-run capital in the economy is 2. To calibrate the stochastic discount factor, we set the real risk-free rate = 1.65% per annum. We set the loading of the stochastic discount factor on the aggregate productivity shock to be $\gamma_x = 0.5$, and the loading of the stochastic discount factor technology frontier shock to be $\gamma_s = 8$ by matching the average market excess returns.

Adoption: parameters varying across time. For parameters with heterogeneity across time and across groups of firms, we calibrate them separately for the pre-2000 and the post-2000 economies. In the model, the mean level of the technology frontier $\bar{s}(\mathcal{T})$, the operating production costs $f_o(\mathcal{F}, \mathcal{T})$, and the fixed technology adoption cost f_a together determine the average markup, the dividend ratio, and the adoption rate (the fraction of firms adopting the frontier technology S_t). However, direct empirical estimates of firms' technology decisions are not available. We rely on findings from a European Investment Bank survey by Rückert, Weiss, and Veugelers (2020), which indicates that digital technology adoption ranged between 67% to 80% according to a 2018 survey. For the post-2000 economy, we set the adoption rate at 70%; for the pre-2000 economy, we interpolate the technology adoption rate by assuming a linear relationship between adoption frequency and mentions of technology adoptions in 10-K filings, resulting in an estimated adoption rate of 41%.

For the pre-2000 economy, we set the mean level of the technology frontier $\bar{s}(\mathcal{T})$ to -0.80 together with the operating production costs $f_o(\mathcal{F}, \mathcal{T}) = 0.075$ and the adoption cost $f_a = 5.6$ so that the implied markup is 1.65, the dividend ratio at 0.18, and the adoption rate at 38%, all of which are close to the data. For the average moments in the post-2000 economy, we increase the mean level of the technology frontier $\bar{s}(\mathcal{T})$ to 0.21 and keep other parameters unchanged to match the adoption rate 70%. The model implied markup is 2.11 and dividend ratio is 0.25, which are close to the data.

Adoption: parameters varying across firms To capture the heterogeneity across groups with different markups, we vary the marginal production costs $f_o(\mathcal{F}, \mathcal{T})$ which determines the marginal benefit of technology adoptions and the elasticity of firms' demand function $\xi(\mathcal{F}, \mathcal{T})$ across firms in the post-2000 economy. We pin down these two parameters to match the markup and dividend rate of the low and high markup firms in the data. Specifically, for low the markup group, we set $f_o = 0.335$ and $\xi = 7$ so that the implied markup is 1.42 and the implied dividend ratio is 0.11, close to the data counterpart of 1.20 and 0.11; for the high markup group, we set $f_o = 0.035$ and $\xi = 4.1$ so that the implied markup is 3.25 and the implied dividend ratio is 0.31, close to the data moment of 3.26 and 0.36.

4.2 Policy functions

This section studies the policy functions of the model. We focus on the technology adoption decision of the firm (ϕ_t). Figure 6 plots the technology adoption policy against the technology capital (n_{t-1}) while holding other states at the long-run average level. We scale the technology capital n_{t-1} by $\max n_{t-1}$ for an easy comparison across different calibrations. We see from the top panel (pre-2000 calibration) that when the current technology capital is small, firms choose to adopt the frontier technology as the adoption benefit is large. While for firms with large current technology capital which are close to or higher than the frontier, these firms choose not to adopt since the adoption benefit is small. The middle and bottom panels shows the adoption policies in the post-2000 calibration, where the middle panel is the low adoption benefit (higher f_o, lower firm's market power, low markup) group and the bottom panel is the high adoption benefit group (lower f_o, higher firm's market power, high markup). The low markup group's adoption region becomes smaller compared to the top panel since the firms are subject to the larger cost $f_o(\mathcal{F}, \mathcal{T})$ comparing to that in the economy before 2000. The bottom panel shows that the high adoption benefit group's adoption region becomes larger since these these firms face a smaller cost $f_o(\mathcal{F}, \mathcal{T})$.

Figure 6 also plots the adoption decisions with different aggregate capital K. Recall that K captures the industry state which firms take into account in strategic compitions with other firms. We see that in the pre-2000 economy, adoption decreases in aggregate capital for firms with medium current technology capital n_{t-1}. This is intuitive: high aggregate capital represents more intense competition in the model since it leads to lower aggregate industry price index P and lower marginal revenue. This effect also implies less benefit for technology adoption as the future marginal revenue is lower for firms that not too far from the frontier. We also see the same pattern in the middle figure of the low adoption group in the post-2000 economy. Interestingly, for the high adoption group of the post-2000 economy, the optimal adoption decision does not vary with aggregate capital, this is because the production cost f_o is low and the firm's market power is high that the benefit of technology adoption is sufficiently high across different values of K.

Figure 7 presents the model implied markups against the technology frontier $\frac{S_t}{\max S_t}$. When the current technology frontier is small (low efficiency), the firms do not adopt technology since the benefit from reducing production cost is small; as a result markup stay unchanged. When the current technology frontier is large (high efficiency), the benefit from technology adoption is large since the operating cost reduction is large, thence firms choose to adopt the frontier technology, which leads to an increase in markup. Comparing to the economy before 2000, firms in the low adoption group in the post-2000 economy have a smaller markup and less adoption due to the larger production cost $f_o(\mathcal{F}, \mathcal{T})$ and lower firm's market power. While firms in the high adoption group of the post-2000 economy have larger markups and more adoptions due to the smaller production cost $f_o(\mathcal{F}, \mathcal{T})$ and higher firm's market power.

We also see jumps in markups; this happens because for a given current technology capital, if the firms starts to adopt a higher technology frontier, the difference of $S_t - (1-\delta_n)n_{j,t-1}$ is larger, which implies a larger relative jump in markups. In other words, the relative jump in markups upon the technology adoption choice cutoff decreases in the adoption rate.

4.3 Dynamics of markups and the value premium

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

4.3.1 Pre-2000 economy

Table 6 reports the model implied moments for the pre-2000 economy. Overall the model fits the data reasonably well. The model implied market returns and the risk-free rate are 5.4% and 1.65%, close to the data moments of 6% and 1.47%; the model implied Sharpe ratio is 0.23, somewhat smaller than the data at 0.39. Furthermore, the dividend ratio in the model is 0.19, close to the empirical counterpart at 0.18. More importantly, the model generates a large value premium at 5.3%, close to the data counterpart of 5.7% and a markup at 1.65, close to the data of 1.66 as well. In the model, value firms are more exposed to the frontier shock than growth firms, because they lag behind the technology frontier and cannot catch up with it due to the adoption cost. As a result, they are riskier. Furthermore, the model also generates a sizable spread in the CAPM alpha of 2.9% for the value premium, consistent with the failure of the CAPM in capturing the value premium in the data, although the magnitude is somewhat short off the data. Intuitively, the aggregate technological frontier shock drives the cross-sectional risk dispersion, while the market is driven more by the aggregate productivity shock, and hence the CAPM does not capture the entire cross-sectional variations in the 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 ($\bar{s}(\mathcal{T})$) that benefits all firms. The increase of the efficiency of the aggregate technology frontier lead to a aggregate markup of 2.11 and adoption rate 70%, which are close to the data.

In addition, to capture the heterogeneity across groups with different markups, we vary the marginal production costs ($f_o(\mathcal{F}, \mathcal{T})$) and the demand elasticity ($\xi(\mathcal{F}, \mathcal{T})$) to generate low and high markup groups. The heterogeneous marginal production costs directly imply different adoption benefits. In particular, lower marginal production costs imply higher technology adoption benefit leading firms to more likely to adopt the frontier technology (75% adoption rate in the model); moreover they are also the firms with low demand elasticity (high market power). As a result they are the ones with the higher markup at 3.25, close to the data moment of 3.26, which in turn drives the aggregate markup to increase. Low marginal production costs and high market power also lead to a high dividend payout ratio at 0.31, close to the data moment at 0.36. Furthermore, due to the low operating costs for the high markup firms, the dispersion of these firms' exposure to the technology frontier shock decreases relative to the pre-2000 economy, which leads to a small value premium of 1.3%, somewhat higher than the data of -3%.

In contrast, firms with higher marginal production costs have lower technology adoption benefits, and hence lower likelihood to catch up with the technology frontier as adoption is too costly for them. Therefore, they still operate with the old technology and incur large operating costs. Moreover, these firms are also those with high demand elasticity (low market power). As a result, their markups remain low at 1.4, close to 1.2 in the data. In addition, the dividend payout ratio is also low at 0.11, the same as the data. Furthermore, high production costs for the low markup group of firms imply that the risk dispersion (exposures to the aggregate frontier shock) remains large. Hence the value premium remains sizable at 6.1%, close to the data at 7.4%. Taken together, this analysis shows that the increase in the technology frontier efficiency and the heterogeneities in technology adoption benefits and firm demand elasticities are quantitatively important to generate the decline of the value premium and the rise of the markup, both of which are primarily driven by the high markup firms.

5 Inspecting and testing the mechanism

In this section we perform several counterfactual analyses to inspect the economic forces driving the overall fit of the model. Additionally we also conduct empirical tests for the model's mechanism on technology adoption and markups.

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, $\bar{s}(\mathcal{T})$. To examine the impact of this heterogeneity on the changes in the value premium and markups, we reduce the increase in the efficiency of the aggregate technology frontier in the post-2000 economy by 50% while keeping the cross-firm heterogeneities unchanged. Table 7 reports the result (the row "Low efficiency increase in frontier"). We find that the markup of high markup firms drops to 2.7, counter-factually too small compared with the data, whereas the value premium increases to 1.9%, bigger than the baseline and the data. This is intuitive: because the efficiency of the frontier technology does not improve as much as in the baseline model, the effective technology adoption fraction decreases which leads to a higher realized marginal costs of production, and hence a lower average markup and a higher value premium than the baseline. On the other hand, the low markup firms' value premium increases to 17.34%, way too high than the data, and their markups fall compared to the baseline.

5.2 The role of cross-firm heterogeneity of adoption benefits

Another key heterogeneity of the model is the cross-group difference in the technology adoption benefit, which is determined by the operating cost parameter $f_o(\mathcal{F}, \mathcal{T})$. Intuitively, the lower $f_o(\mathcal{F}, \mathcal{T})$ is, the higher the adoption benefit is given the technology frontier shock. To investigate the impact of the cross-group adoption benefit heterogeneity on the value premium and markups across firms, we set $f_o(\mathcal{F}, \mathcal{T}) = 0.075$ for both high and low markup groups; it is also the same as the baseline parameter value in the pre-2000 economy. The row "No heterogeneity in adoption benefits" in Table 7 reports the result. We find that the value premium of the high markup group increases to 2.4%, higher than the baseline and the data, while the markup decreases to 2.3 much lower compared to the baseline and the data. This is intuitive: because the marginal costs of the high markup group is bigger than the baseline, causing the average markup to be lower than the baseline model; in the meantime, the operating costs channel remains quantitatively important for the high markup group, leading to a big value premium, opposite to the data. For low markup group of firms, the value premium falls to 5.5%, smaller than the baseline and the data, while markups rises to 1.95 much higher than the baseline and the data. Taken together, shutting down heterogeneity in adoption benefits results in an 80% reduction in the markup difference and a 35% decrease in the value premium difference between low and high markup groups relative to the baseline.

5.3 The role of cross-firm heterogeneity of firm demand elasticity

In the model, firms face a downward sloping demand curve where the market power is determined by the demand curve elasticity parameter ξ. In this section, we set the firm demand elasticity ξ the same across low and high markup groups at 5. The row of "No heterogeneity in firm demand elasticity" in Table 7 reports the result. We find that the value premium of the high markup group increases to 1.54%, slightly higher than the baseline and the data, while the markup decreases to 3, slightly lower compared to the baseline and the data. For low markup group of firms, the value premium falls to 5.2%, smaller than the baseline and the data, while markups rises to 1.54, slightly higher than the baseline and the data. Taken together, removing heterogeneity in demand elasticity reduces the markup and value premium differences between low and high markup groups by 20% and 25%, respectively. These decreases are smaller than those caused by shutting down heterogeneity in adoption benefits, implying that the heterogeneity in adoption benefits plays a first-order effect quantitatively.

5.4 The role of industry demand elasticity

Lastly, we examine the impact of the industry demand elasticity (η) on quantities and prices in the model, which is through changes in revenue due to changes in aggregate price P as in equation (7). This analysis can be interpreted as a way to understand the cross-industry substitutability on value premium and markups. Specifically, we lower η from 4 to 3, implying that the industry has more market power relative to other industries. In the row of "High industry market power" in Table 7, we see that value premium drops significantly for the pre-2000 economy, and for both high and low markup groups in the post-2000 economy as well, while the change in the markup is small compared to the baseline calibration. This is intuitive as the industry is more insulted from aggregate shocks with more market power, within industry risk dispersion decreases, while the markup is mainly driven by the within industry marginal production cost and output price, and hence is less affected.

5.5 Testing the technology adoption channel

In this section, we empirically test our model's main prediction that the rise of markup and the decline of value premium concentrate among companies that most likely to adopt new technologies. To quantify technology adoption, we conduct textual analysis by counting the appearance technology related keywords in a company's annual reports.[4] We identify firms that mention these keywords most frequently as most likely to adopt new technology. To demonstrate how technology adoption affects markup and value premium, we sort firms into three groups each year based on the size-adjusted number of keyword appearance in their annual reports and measure each group's markup and value premium. Specifically, we first sort firms into two groups, large and small, based on whether their market cap is above

[4]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.

the cross-sectional median.[5] We then sort firms within each size group into terciles based on how many times technology-related keywords appear in their annual reports. We label these terciles as low-adoption, mid-adoption, and high-adoption firms. Figure 5 plots the average markup of firms in each tercile. This figure and Table 8 Panel A clearly show that high-technology-adoption firms have the largest increase in markup, from 1.84 in 1994 to 2.88 in 2020, whereas low-technology-adoption firms experience very little change in their markup during the past twenty five years. Table 8 Panel B reports the value premium within each technology-adoption tercile. It shows that over the past twenty years, firms within the lowest technology adoption tercile continue to have a sizable value premium of 0.56% per month with a t-statistic of 1.74, while firms in the highest technology adoption tercile have an insignificant value premium. The difference in value premium between the two groups of firms is large, at 1.01% per month (t-statistic: -2.33). Overall, these results confirm the model's main prediction that technology adoption plays a significant role in explaining both the rise of markup and the decline of value premium.

6 Conclusion

We provide a unified explanation for two important secular trends during the last few decades: the decline of the value premium and the rise of the markup. We show that these two trends are closely connected. Empirically, we find that the decline of the value premium is primarily driven by firms with high markups, while the value premium remains sizable in the low markup firms. Moreover, the rise of the aggregate markup is also driven the same high markup firms that drive the decline of the value premium. We develop a dynamic model featuring technological frontier shocks and costly technology adoption. We show that the model quantitatively captures the two trends observed in the data. The key insight is that the rise in the efficiency of the aggregate technology frontier and firms' heterogeneous

[5] 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.

technology adoption benefits are crucial to jointly capture the decline in the value premium, the rise of the markups, and the cross-sectional difference in these two trends.

This paper also has broad implications for macroeconomics, finance, and IO. Our findings suggest that technology changes can have a significant impact on the changes in asset prices and markups. In addition, our analysis shows that risk premiums are an important determinants of firms' adoption decisions, which in turn affects the firms' markup. Lastly our results also show that the economic driving forces for the recent change in the industrial structure, e.g., the rise in the aggregate markup, is closely related to the change in the risk premium. It is important to understand these trends jointly in a unified framework.

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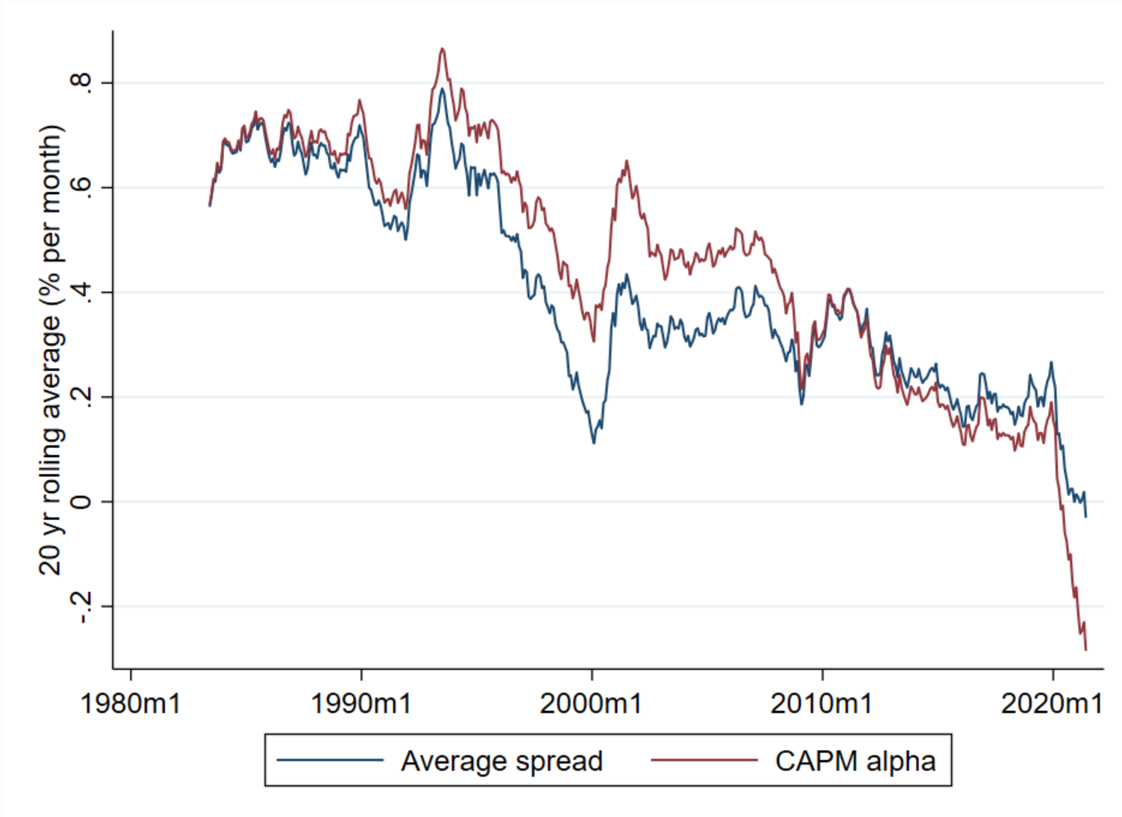
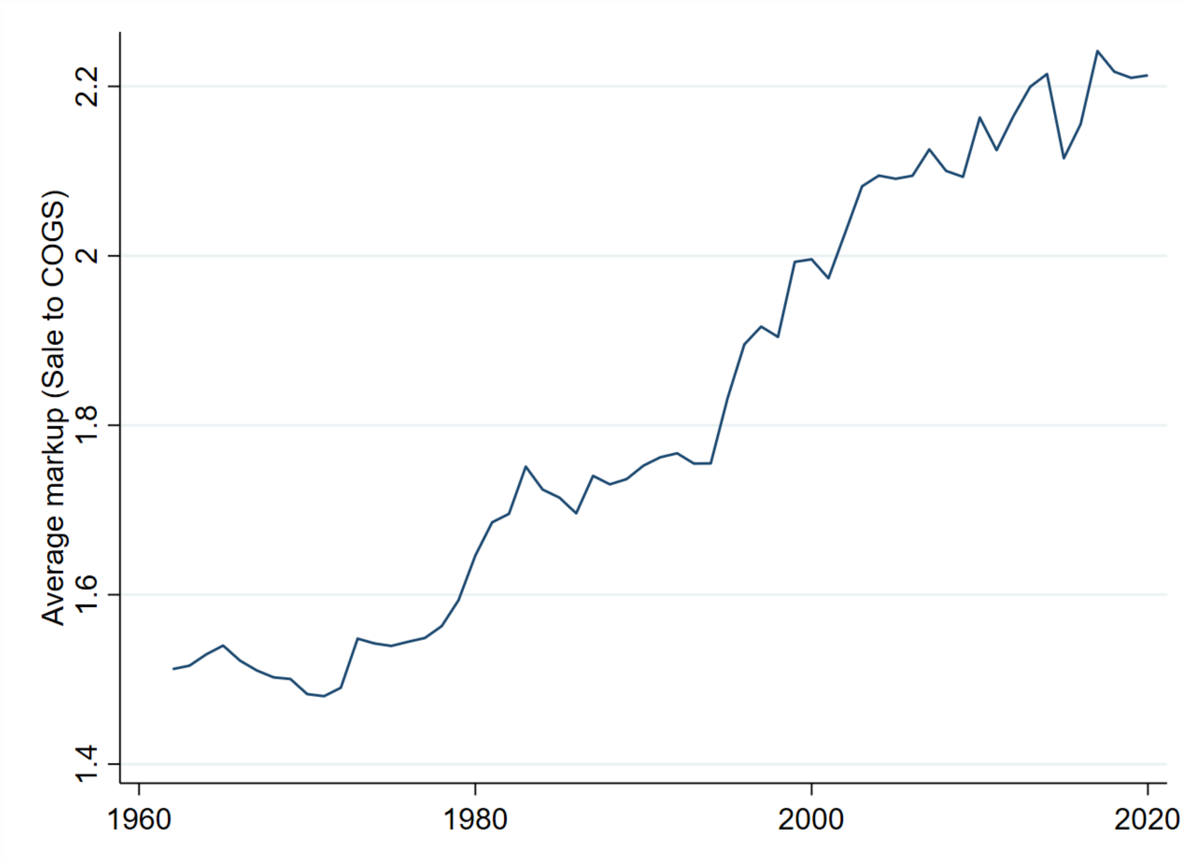
Figure 1: Rolling 20-year average value premium



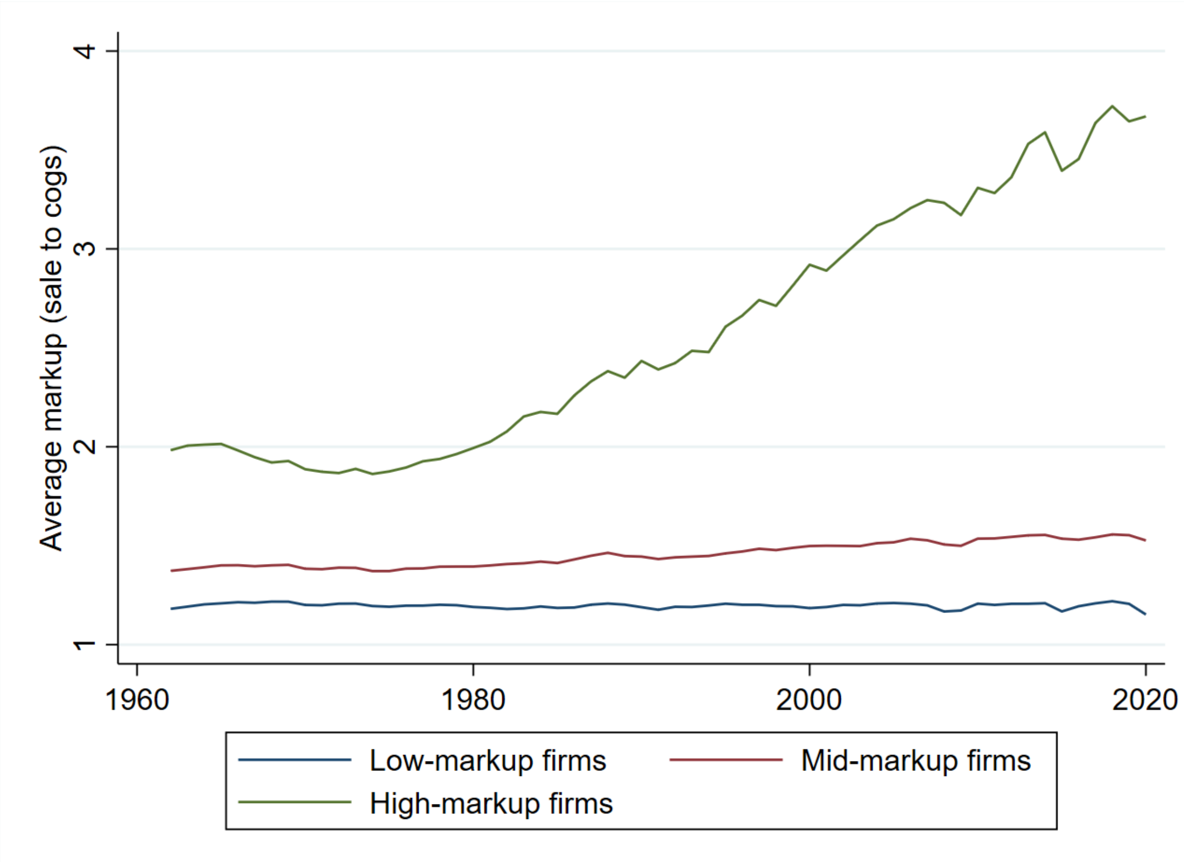
This figure plots 20-year rolling average return and CAPM alpha of top book-to-market quintile (value stocks) minus bottom book-to market-quintile (growth stocks). The sample period is from 1963m7 to 2021m6.

Figure 2: Aggregate markup



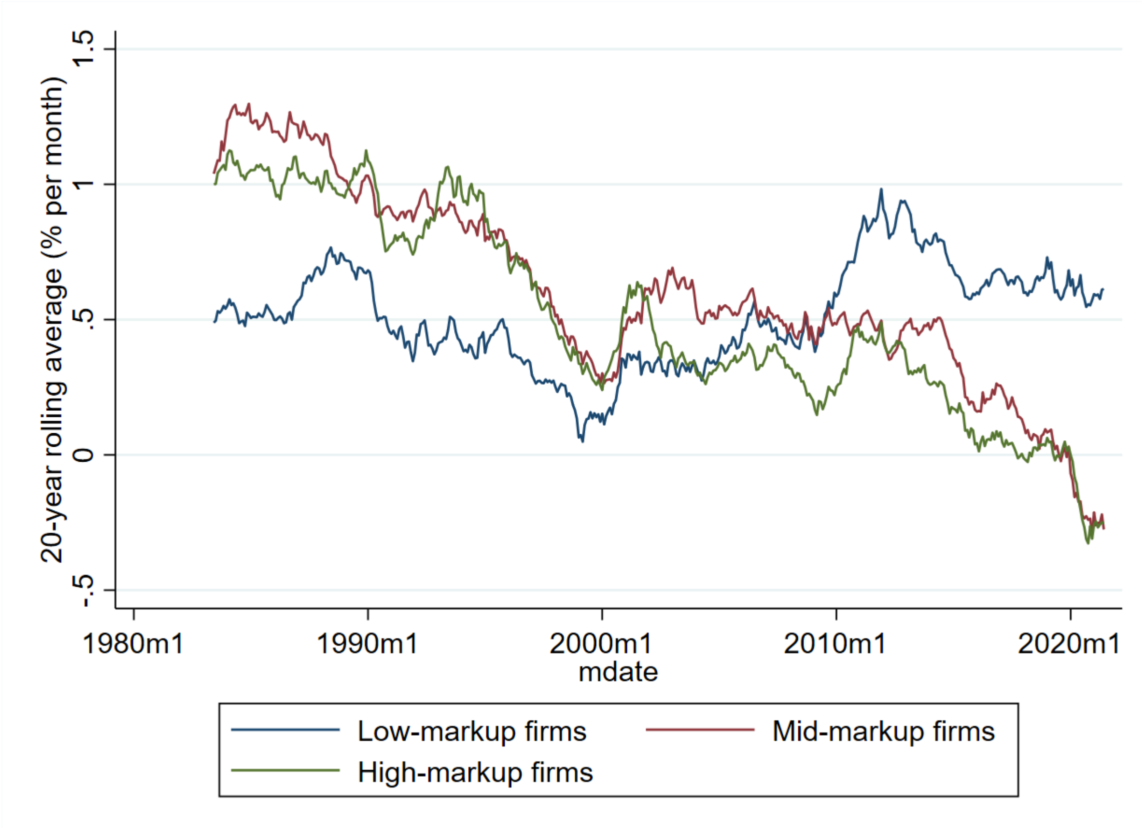
This figure plots the average markup of US public firms (excluding utilities and financials) from 1962 to 2020. We measure markup of a firm as the ratio between its revenue and cost of goods sold.

Figure 3: Average markups of high-, mid-, and low-markup companies



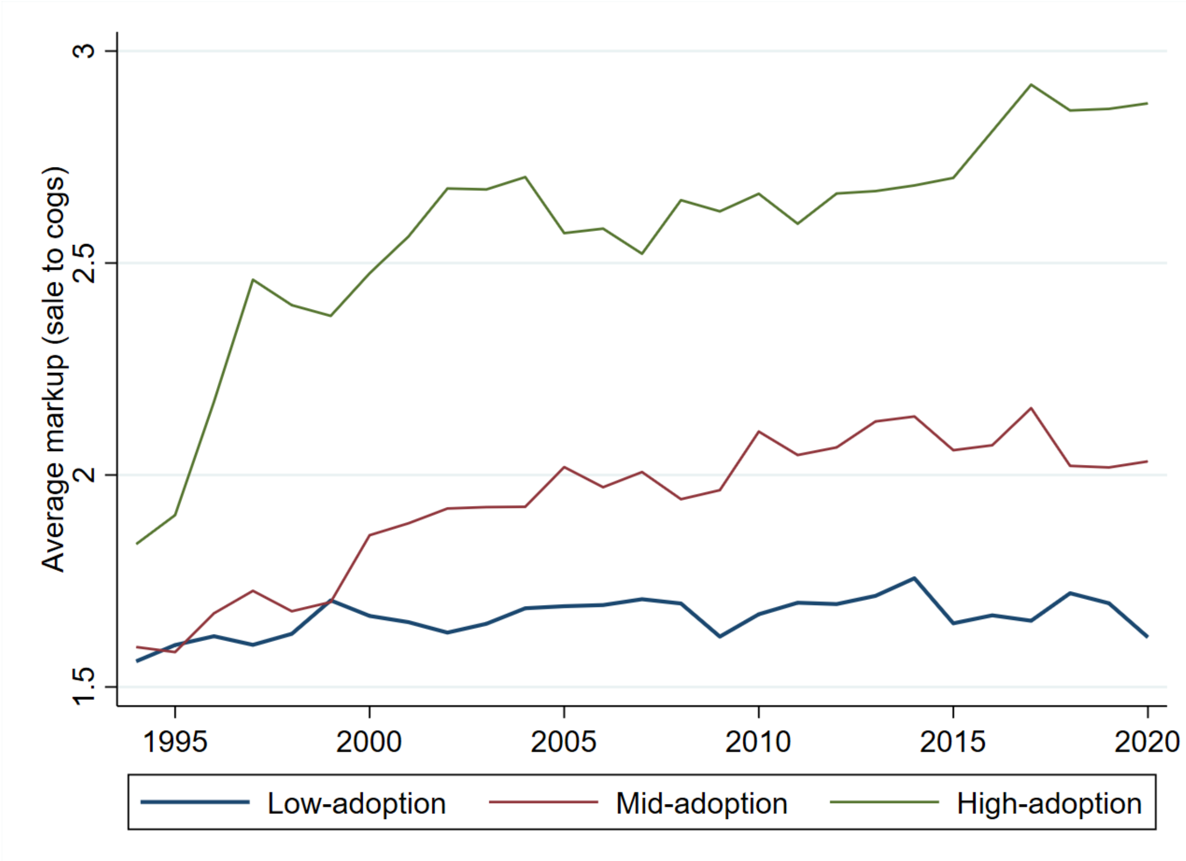
This figure plots the average markup of low, mid and high-markup firms from 1962 to 2020. Low, mid and high-markup firms are defined as firms in the bottom, middle and top NYSE tercile in terms of markup. We measure themarkup of a firm as the ratio between its sales and cost of goods sold.

Figure 4: Value premium of high-, mid-, and low-markup companies



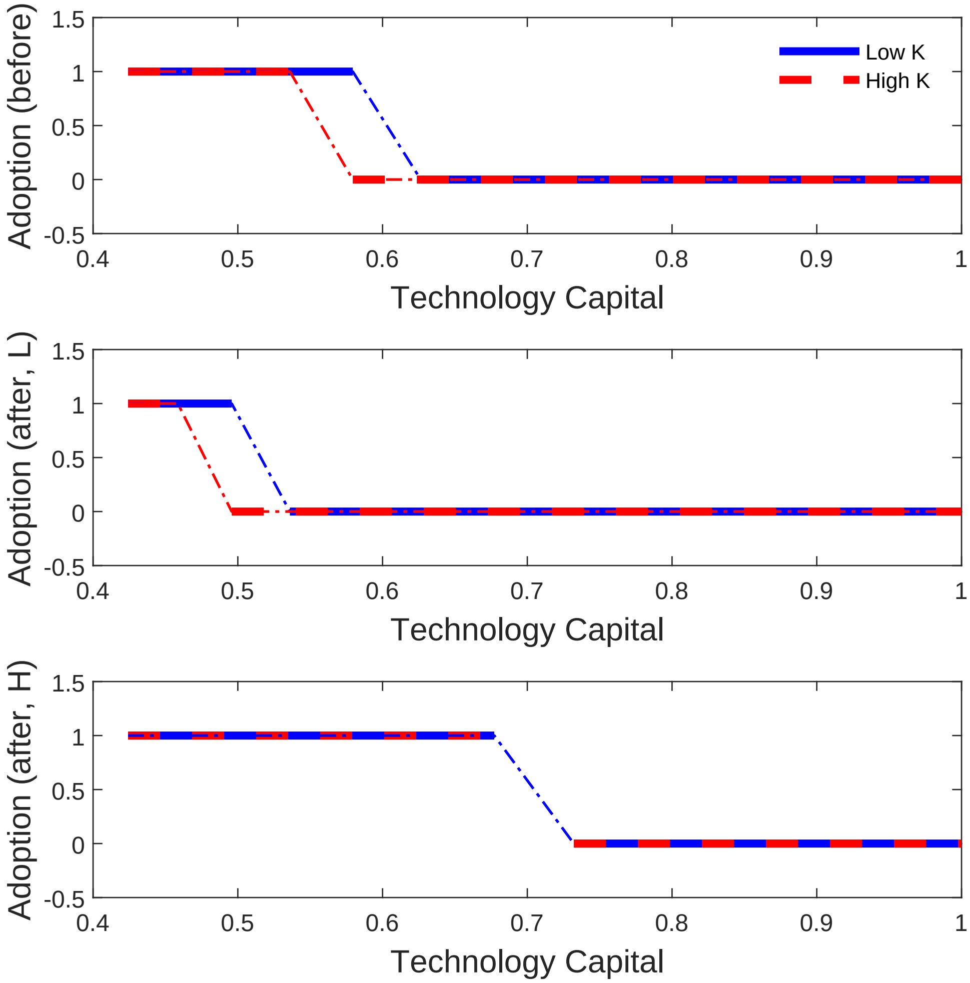
This figure plots the 20-year rolling average value premium among high-, mid-, and low-markup firms. We sort companies into terciles based on their markup and into quintiles based on their book-to-market ratio. We compute value premium in each markup tercile as the value-weighted return of top book-to-market firms minus the value-weighted return of bottom book-to-market firms in the tercile. The sample period is from 1963m7 to 2021m6.

Figure 5: Average markup and technology adoption



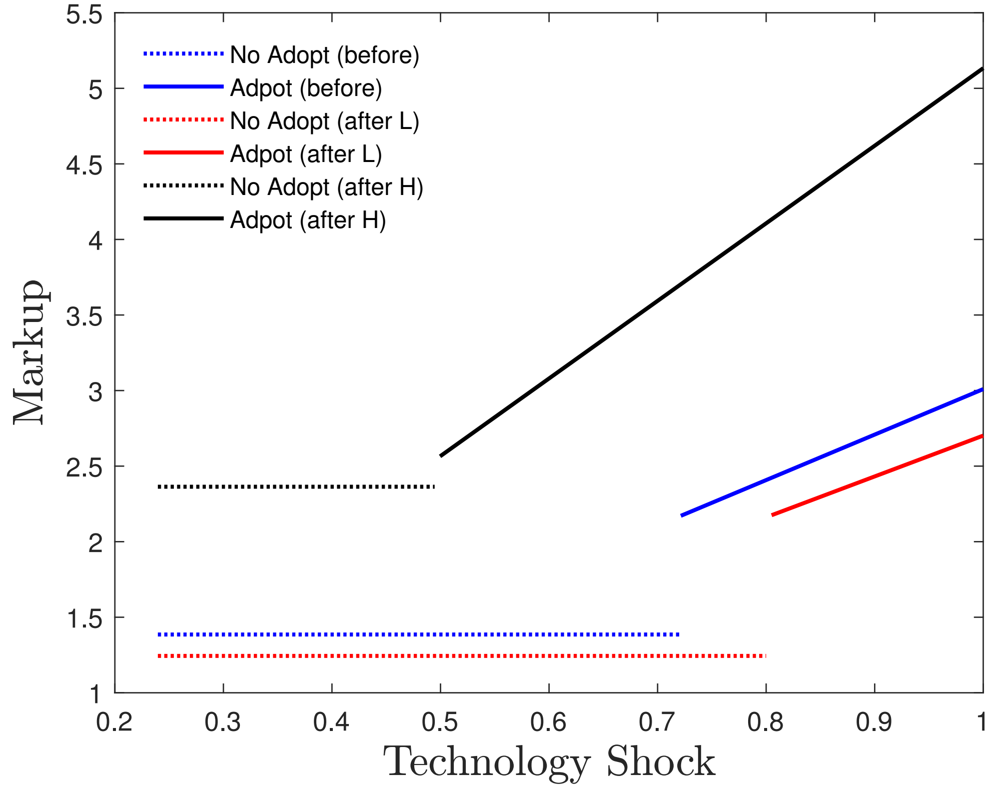
This figure plots the average markup of firms sorted by the size-adjusted count of technology related keywords in annual report. We first sort companies into two groups by market cap. Within each size group, we sort companies into terciles by the number of technology related keywords in their annual report. We label firms with low (mid, or high) appearance of technology keywords as low- (mid- or high-) adoption firms. We then measure the average markup of firms in each technology-adoption tercile. The sample period is from 1994 to 2020.

Figure 6: Technology adoption policies



This figure shows the technology adoption policies with respect to the scaled technology capital $\frac{n_{t-1}}{\max n_{t-1}}$. The three panels (from top to bottom) are plotted under the economy before 2000, the low adoption benefit group after 2000, and the high adoption benefit group after 2000 with different values of aggregate capital K, respectively. Other state variables are chosen at the long-run mean of the corresponding economies. All parameters are reported in Table 5.

Figure 7: Markup



This figure plots the markup with respect to the scaled technology frontier shock $\frac{S_t}{\max S_t}$. The blue lines, the red lines, and the black lines are plotted under the economy before 2000, the low group after 2000, and the high group after 2000 respectively. The solid lines indicate the firms adopt the new technology, while the dashed lines indicate there is no adoption. Other state variables are chosen at the long-run mean of the corresponding economies. All parameters are reported in Table 5.

Table 1: Decline in the value premium

This table reports the performance of the HML factor (in columns 1 and 2), the top-minus-bottom BM quintile (in columns 3 and 4), big cap HML factor (in columns 5 and 6), and small cap HML factor (in columns 7 and 8) in different sample periods. Panel A reports the performance from 1963m7 to 2001m6. Panel B reports the performance from 2001m7 to 2021m6. Panel C uses all sample period from 1963m7 to 2021m6 with a dummy variable that indicates if a month is after 2001m6. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HML factor		Top - Bottom		Big HML		Small HML	
Panel A: 1963m7 to 2001m6								
Mkt-RF		-0.27***		-0.15***		-0.18***		-0.35***
		(-6.89)		(-2.74)		(-4.15)		(-8.83)
Constant	0.45***	0.58***	0.48***	0.55***	0.33**	0.42***	0.56***	0.74***
	(3.26)	(4.70)	(2.91)	(3.44)	(2.29)	(3.04)	(3.64)	(5.49)
Observations	456	456	456	456	456	456	456	456
Adjusted R^2	0.000	0.167	0.000	0.033	0.000	0.068	0.000	0.224
Panel B: 2001m7 to 2021m6								
Mkt-RF		0.12**		0.36***		0.31***		-0.07
		(2.09)		(4.51)		(4.50)		(-1.15)
Constant	-0.07	-0.16	-0.04	-0.30	-0.21	-0.43*	0.07	0.12
	(-0.39)	(-0.81)	(-0.14)	(-1.13)	(-0.92)	(-1.93)	(0.34)	(0.54)
Observations	240	240	240	240	240	240	240	240
Adjusted R^2	0.000	0.031	0.000	0.144	0.000	0.152	0.000	0.005
Panel C: 1963m7 to 2021m6								
After 2001m6	-0.52**	-0.49**	-0.51*	-0.52*	-0.54**	-0.53**	-0.49*	-0.44*
	(-2.25)	(-2.06)	(-1.65)	(-1.67)	(-2.01)	(-1.97)	(-1.95)	(-1.74)
Mkt-RF		-0.14***		0.02		-0.02		-0.25***
		(-3.76)		(0.47)		(-0.37)		(-7.42)
Constant	0.45***	0.51***	0.48***	0.47***	0.33**	0.34**	0.56***	0.69***
	(3.26)	(4.03)	(2.91)	(2.83)	(2.29)	(2.35)	(3.64)	(5.04)
Observations	696	696	696	696	696	696	696	696
Adjusted R^2	0.006	0.048	0.003	0.002	0.005	0.004	0.004	0.124

Table 2: Increase in markup

This table reports the change in aggregate markup for all firms in Panel A and in each markup sorted tercile in Panel B. We measure each firm's individual markup as its revenue divided by cost of goods sold. We measure the weighted average markup of all firms in each year using cost of goods sold as weights, equal weights, or sales as weights. In Panel A, we regress annual average markup on a dummy variable indicating whether a year is after 2001 (inclusive). In Panel B, we sort firms into three groups based on their individual markup and measure cost-weighted average markup for each group. We exclude financial firms and utilities from the calculation. The sample period is from 1962 to 2020. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: market wide markup

	Cost-weighted	Equal-weighted	Sales-weighted
VARIABLES		Average markup	
After 2001	0.08***	0.47***	0.29***
	(9.11)	(13.27)	(14.24)
Constant	1.41***	1.66***	1.52***
	(282.56)	(80.60)	(127.99)
Observations	59	59	59
Adjusted R^2	0.586	0.751	0.777

Panel B: markup by group

	Low markup tercile	Mid markup tercile	High markup tercile
VARIABLES		Equal-weighted markup	
After 2001	-0.00	0.11***	1.14***
	(-0.12)	(12.53)	(14.36)
Constant	1.20***	1.42***	2.19***
	(565.15)	(278.49)	(47.25)
Observations	59	59	59
Adjusted R^2	-0.017	0.729	0.780

Table 3: Excess return and CAPM alpha of BM and markup sorted portfolios

This table reports the average return and CAPM alpha of double sorted portfolios in different sample periods. We sort firms based on their markup, measured sales divided by cost of goods sold, into terciles and based on their book-to-market ratio into quntiles. We use NYSE cut-offs to create portfolios. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	Lo BM	2	3	4	Hi BM	Hi-Lo
Panel A: average excess return from 1963m7 to 2001m6						
Low Markup	0.32	0.42*	0.57**	0.63***	0.76***	0.44**
	(1.12)	(1.74)	(2.43)	(2.64)	(2.98)	(2.14)
Mid markup	0.29	0.52**	0.62***	0.82***	1.08***	0.79***
	(1.05)	(2.13)	(2.77)	(3.65)	(4.25)	(4.01)
High Markup	0.51**	0.62***	0.55**	0.79***	1.29***	0.78***
	(2.14)	(2.81)	(2.55)	(3.33)	(4.58)	(3.62)
High - Low	0.18	0.20	-0.01	0.16	0.53***	0.34
	(1.24)	(1.39)	(-0.08)	(0.94)	(3.03)	(1.53)
Panel B: average excess return from 2001m7 to 2021m6						
Low Markup	0.49	0.85***	0.74**	0.75*	1.11**	0.61**
	(1.47)	(3.12)	(2.12)	(1.94)	(2.42)	(2.04)
Mid markup	1.06***	0.82**	0.90**	0.92**	0.78	-0.28
	(3.02)	(2.57)	(2.47)	(2.54)	(1.63)	(-0.78)
High Markup	0.83***	0.79**	0.64*	0.61*	0.57	-0.25
	(3.01)	(2.54)	(1.94)	(1.67)	(1.30)	(-0.79)
High - Low	0.33*	-0.06	-0.10	-0.14	-0.53*	-0.87***
	(1.88)	(-0.27)	(-0.50)	(-0.66)	(-1.74)	(-2.65)
Panel C: average CAPM alpha from 1963m7 to 2001m6						
Low Markup	-0.30**	-0.09	0.09	0.12	0.25*	0.55***
	(-2.34)	(-0.73)	(0.73)	(1.11)	(1.79)	(2.80)
Mid markup	-0.32***	-0.03	0.14	0.37***	0.58***	0.90***
	(-2.97)	(-0.28)	(1.38)	(3.02)	(4.01)	(4.72)
High Markup	-0.02	0.13	0.10	0.33**	0.76***	0.77***
	(-0.19)	(1.55)	(0.92)	(2.38)	(4.39)	(3.60)
High - Low	0.28*	0.21	0.01	0.20	0.51***	0.23
	(1.97)	(1.53)	(0.09)	(1.17)	(2.94)	(1.04)
Panel D: average CAPM alpha from 2001m7 to 2021m6						
Low Markup	-0.28*	0.28*	-0.08	-0.12	0.09	0.37
	(-1.78)	(1.71)	(-0.50)	(-0.64)	(0.37)	(1.26)
Mid markup	0.25	0.07	0.03	0.08	-0.22	-0.46
	(1.57)	(0.52)	(0.19)	(0.50)	(-0.75)	(-1.28)
High Markup	0.17	0.07	-0.12	-0.21	-0.33	-0.49
	(1.64)	(0.50)	(-0.79)	(-1.11)	(-1.20)	(-1.61)
High - Low	0.45**	-0.21	-0.05	-0.09	-0.42	-0.86**
	(2.44)	(-0.99)	(-0.25)	(-0.43)	(-1.27)	(-2.44)

Table 4: Markup and change in value premium

This table reports the change in value premium among low-markup firms (in columns 1 and 5), mid-markup firms (in columns 2 and 6), and high-markup firms (in columns 3 and 7). Columns 4 and 8 report the difference in value premium between high- and low-markup firms. In Panel A, we sort companies into terciles based on their markup and into quintiles based on their book-to-market ratio. We use NYSE cut-offs. We compute value premium in each markup tercile as the value-weighted return of top book-to-market quintile minus the value-weighted return of bottom book-to-market quintile in the tercile. In Panel B, we sort industries into terciles based on industry markup and pool firms together in each tercile. We estimate the change in value premium with a dummy variable indicating whether a month is after June 2001. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	Mid	High	High-Low	Low	Mid	High	High-Low
Panel A: change in value premium by firm-level markup								
After 2001m6	0.18	-1.07***	-1.04***	-1.21***	0.18	-1.06***	-1.06***	-1.25***
	(0.49)	(-2.65)	(-2.68)	(-3.05)	(0.50)	(-2.59)	(-2.79)	(-3.12)
Mkt-RF					-0.03	-0.05	0.12**	0.15***
					(-0.61)	(-0.87)	(2.11)	(3.03)
Constant	0.44**	0.79***	0.78***	0.34	0.45**	0.82***	0.72***	0.27
	(2.14)	(4.01)	(3.62)	(1.53)	(2.26)	(4.23)	(3.33)	(1.22)
Observations	696	696	696	696	696	696	696	696
Adjusted R^2	-0.001	0.010	0.009	0.012	-0.001	0.011	0.020	0.029
Panel B: change in value premium by industry markup								
After 2001m6	0.14	-0.86*	-1.03***	-1.17**	0.15	-0.85*	-1.05***	-1.21***
	(0.34)	(-1.96)	(-2.71)	(-2.56)	(0.36)	(-1.92)	(-2.80)	(-2.61)
Mkt-RF					-0.05	-0.05	0.11**	0.16**
					(-0.83)	(-0.76)	(1.97)	(2.56)
Constant	0.60***	0.68***	0.79***	0.20	0.62***	0.70***	0.74***	0.12
	(2.68)	(2.94)	(3.53)	(0.78)	(2.79)	(3.13)	(3.30)	(0.47)
Observations	696	696	696	696	696	696	696	696
Adjusted R^2	-0.001	0.005	0.009	0.008	-0.001	0.005	0.018	0.022

Table 5: Parameter values

This table presents the calibrated parameter values of the baseline model.

A: Common Parameters

Parameter	Symbol	Value
Technology: general		
Industry demand elasticity	η	4
Rate of depreciation for capital	δ_K	0.04
Rate of depreciation for capital	δ_N	0.075
Technology: adjustment costs		
Sale value of capital	c_k	0
Fixed technology adoption cost	f_a	5.6
Stochastic processes		
Persistence coefficient of aggregate productivity	ρ_x	0.985
Conditional volatility of aggregate productivity	σ_x	0.055
Average level of firm-specific productivity	$\bar{z}$	-0.3
Persistence coefficient of firm-specific productivity	ρ_z	0.94
Conditional volatility of firm-specific productivity	σ_z	0.2
Persistence coefficient of operation cost	ρ_s	0.86
Conditional volatility of operation cost	σ_s	0.07
Real risk-free rate	r_f	0.004
Loading of the SDF on aggregate productivity shock	γ_x	0.5
Loading of the SDF on the operation cost	γ_s	8

B: Heterogeneity in parameters

Parameter	Symbol	Before 2000	After 2000	
			L	H
Firm demand elasticity	$\xi(\mathcal{F}, \mathcal{T})$	5	7	4.1
Long-run mean of technology frontier shock	$\bar{s}(\mathcal{T})$	-0.80	0.21	0.21
Operation costs	$f_o(\mathcal{F}, \mathcal{T})$	0.075	0.335	0.035

Table 6: Selected moments in the data and the model

This table presents the selected moments implied by the baseline model calibration before 2000. We compare the moments in the data ("Data") with moments of simulated data ("Model"). The model-implied moments are the mean value of the corresponding moments across simulations. Value premium is the average returns of the 10th decile minus 1st decile book-to-market portfolio. The reported statistics for the model are obtained from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations.

	Data	Model
Market excess returns	6.05	5.37
Sharpe ratio	0.39	0.23
Risk free rate	1.47	1.65
Markup	1.63	1.65
Value premium	5.72	5.31
CAPM alpha spread of value premium	6.21	2.90
Dividend ratio	0.18	0.18
Adoption rate	0.41	0.38

Table 7: Selected data versus model-implied moments across alternative calibrations

This table presents selected moments of the data and alternative calibrations of the model. Pre-2000 and post-2000 refer to the economy before 2000 and after 2000, respectively. Low and High refer to the low markup and high markup groups, respectively. Low efficiency increase in frontier is the model specification where $\bar{s}(\mathcal{T})$ increases by a half of the baseline model; No heterogeneity in adoption is the model specification where the operating cost parameter $f_o(\mathcal{F}, \mathcal{T}) = 0.075$ as the baseline pre-2000 economy; No heterogeneity in firm's demand elasticity is the model specification where the firm demand elasticity $\xi(\mathcal{F}, \mathcal{T}) = 5$ as the baseline pre-2000 economy; "High industry market power" is the model specification where the elasticity of the demand curve η is set at 3.

Before 2000						After 2000							
						Low				High			
Market returns	SR	Adoption	Dividend ratio	Markup	ValPremium	Adoption	Dividend ratio	Markup	ValPremium	Adoption	Dividend ratio	Markup	ValPremium
Data													
6.05	0.39	0.41	0.18	1.66	5.72	N.A	0.11	1.20	7.37	N.A	0.36	3.26	-3.05
0. Baseline model													
5.37	0.23	0.38	0.19	1.65	5.31	0.20	0.11	1.42	6.09	0.75	0.31	3.25	1.32
1. Low efficiency increase in frontier													
5.37	0.23	0.38	0.19	1.65	5.31	0.12	0.09	1.41	17.34	0.74	0.30	2.69	1.85
2. No heterogeneity in adoption benefits													
5.37	0.23	0.38	0.19	1.65	5.31	0.68	0.22	1.95	5.50	0.69	0.30	2.28	2.36
3. No heterogeneity in firm demand elasticity													
5.37	0.23	0.38	0.19	1.65	5.31	0.20	0.15	1.54	5.17	0.76	0.28	3.03	1.54
4. High industry market power													
6.23	0.29	0.29	0.16	1.64	4.61	0.15	0.09	1.41	1.82	0.66	0.30	3.24	1.24

Table 8: Technology adoption, markup and value premium

This table reports the average markup and value premium of firms within three technology-adoption terciles. To construct these terciles, we first sort firms into two groups based on whether their market cap is above the cross-sectional median. Within each size group, we sort firms into three tercile groups based on the number of appearance of technology-related keywords. We label the three tercile groups as low-, mid-, and high-adoption firms. Panel A reports the average markup of firms in each tercile in 1994 and 2020. Panel B reports the value premium within each tercile from 2001m7 to 2021m6. To measure value premium, we also independently sort firms into quintiles based on their book-to-market ratio. We then measure the return of value firms (i.e. firms in top-BM-quintile) minus the return of growth firms (i.e. firms in bottom-BM-quintile) within each technology-adoption tercile and report the average. The All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A	(1) Low-adoption	(2) Mid-adoption	(3) High-adoption	(4) High-Low
Average markup in 1994	1.56	1.59	1.84	0.28
Average markup in 2020	1.62	2.03	2.88	1.26
Δ in markup	0.06	0.44	1.04	0.98

Panel B	(1) Low-adoption	(2) Mid-adoption	(3) High-adoption	(4) High-Low
Value premium	0.56*	0.15	-0.45	-1.01**
	(1.74)	(0.40)	(-1.27)	(-2.33)
Observations	240	240	240	240

Appendix For Online Publication

A Data Appendix

This section describe additional robustness checks in the data.

A.1 Value premium in alternative sample periods

We first examine the decline of the value premium using alternative sample periods. Table A.1 presents the results. Panel A splits the entire sample into two parts with the cut-off month in June 1993. We create a dummy variable which equals to 1 if the sample is after June of 1993. We then regress various measures of value premium on the after-1993m6 dummy variable. We also control the market factor to compare the CAPM alpha of value premium between the two sample periods. Across all columns in Panel A, the coefficients on the after-1993m6 dummy variable range from -0.24% to -0.53%. This coefficient is statistically significant at the 10% level in five out of the eight columns. Panel B splits the entire sample into two parts with the cut-off month in June 2007. The coefficients on the post-2007m6 dummy variables are more negative in both magnitude and statistical significance. Value premium measured in various ways declined by about 0.8% per month in the post-2007 period comparing to the pre-2007 period. The coefficients in all eight columns are statistically significant at the 5% or 1% level. Panel C splits the sample period with the cut-off month in June of 2001 and excludes 2020 and 2021 from the sample. Excluding 2020 and 2021 is remove the effect of the Covid-19 pandemic on the measurement of value premium. Panel C shows that even before the pandemic, the value premium already has significant decline in the post 2001 period.

A.2 Rise of markup by industry

We verify the trend of markup and the fact that high markup industries experience more increase in markup in Table A.3 and Table A.4. Table A.3 lists the average markup of Fama-French 30 industries (excluding financials and utilities) from 1962 to 2000 and from 2001 to 2020. 22 out of the 28 industries experience an increase in markup in the post-2001 period. Only 6 industries experience a decline in markup. The top three industries with the highest increase in markup are healthcare, personal and business services, and printing and publishing. Industries with most decline in markup are electrical equipment, coal, and business supplies and shipping industries. Table A.4 regresses the increase in average markup of an industry either in level or in percentages on the pre-2001 average level of industry markup. The coefficients are significantly positive, indicating that industries with high markup before 2000 experience higher increase in markup after 2000.

A.3 Alternative measures of markup

We use different measures of markup to verify the robustness of our main results. Table A.5 sorts stocks based on their industry-level markup and book-to-market ratio. Panel A of Table A.5 shows that from 1963m7 to 2001m6, in low-, mid-, and high-markup industries, stocks with high book-to-market ratio deliver higher average returns than stocks with low book-to-market ratio. The difference in the average return of high-minus-low in low-markup and high-markup industries is not statistically significant in this sample period. Panel B of Table A.5 shows that from 2001m7 to 2021m6, only among stocks in low-markup industries, high book-to-market stocks generate significantly higher average return than low book-to-market stocks, whereas among stocks in mid- and high-markup industries, the value stocks do not deliver higher returns than growth stocks. The difference in value premium between low-markup industries and high-markup industries is statistically significant in the post-2001 sample period. Panel C and D reports the CAPM alpha of the double sorted portfolios in the two sample periods. The results are quantitatively similar as Panel A and B. Stocks in low-markup industries generate higher value premium than stocks in high-markup industries.

Table A.6 calcuates markup based on the measure from De Loecker, Eeckhout, and Unger (2020). The results is similar to Table 3 and Table A.5. In the post-2001 sample period, value premium is much higher among low-markup stocks. Table A.7 sorts stocks by book-to-market ratio and operating leverage. Operating leverage is closely related to markup, since high markup firms tend to have lower operating leverage. We find similar results. In the post-2001 sample, periods, stocks with high operating leverage delivers significantly higher value premium than stocks with low operating leverage.

A.4 Robustness to excluding micro-cap stocks

We check whether our results are robust to excluding micro-cap stocks. Table A.8 reports change in value premium among low, mid, and high markup stocks, excluding micro-cap stocks. The results are similar to Table 4. Panel A shows that value premium is statistically significant in all three group of stocks before 2001. Panel B shows that only among low-markup stocks, value premium is statistically significant. Panel C shows that value premium significantly decline among mid- and high-markup stocks. This table shows that our main result is robust to excluding micro-cap stocks. Table A.9 reports similar results using industry markup as the sorting variable when micro-cap stocks are excluded. Value premium significantly declined among mid- and high-markup industries, while it remains stable among low-markup industries.

A.5 Value premium and intangibles

We explore how intangible assets affect value premium. Table A.10 sort stocks by different measures of intangible assets and check if value premium is significantly different in any group of assets after 2001. If intangible assets are the root cause of the disappearance of value premium, we expected value premium to be strong among firms with low level of intangibles. We find this not to be the case. Panel A sort stocks based on R&D expense to sales. In all three groups, value premium is insignificant and the difference in value premium between low R&D firms and high R&D firms is also insignificant. Panel B, C, and D sort firms based on knowledge capital, organizational capital, and total intangible capital to assets. We find that value premium is weak regardless whether firms have high or low intangible capitals.

Table A.11 tests whether including intangible assets in the calculation of book-to-market ratio can improve value premium. Specifically, we add various types of intangible asset to the book value and then divide by the market cap to compute the intangible asset augmented book-to-market ratio. We then sort stocks based on this ratio into quintiles and report the return of each quintile. All three panels of Table A.11 show that stocks with high augmented book-to-market ratio do not deliver higher returns. This shows that accounting for intangible assets in the book value does not revive the value premium in the post-2001 sample period.

A.6 Asset pricing tests

This section reports the result of asset pricing tests. We specify the pricing kernel as

$$M_t = 1 - b_M MKT_t - b_{MG} MG_t$$

where MKT_t is market return in period t and MG_t is the growth in aggregate markup in period t. We use MG_t as a proxy for the frontier shock in the model. We measure MG_t as the difference in annual growth rate between aggregate sales and aggregate cost-of-goods-sold of all companies in COMPUSTAT (exclude financials and utilities). Table A.12 reports the result of asset pricing tests using various sets of testing assets. Both Panels A and B show that MG_t is positively priced in the cross-sectional with t-statistics on MG_t ranging between 1.86 and 2.32.

B Numerical Algorithm

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

B.1 Solving the monopolistic competitive equilibrium

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

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

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

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

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

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

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

Bellman equation is given by

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

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 ϵ_Γ, then stop and exit the algorithm.

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

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

Once the discrete state space is available, the conditional expectation can be carried out simply as a matrix multiplication. Finally, we use a simple discrete global search routine in maximizing the firm's problem.

To set the grid of the technology capital $n_t = \log(N_t)$, we let $n_{nN} = \bar{s}(\mathcal{T}) + 3\sigma_s$. To make sure the technology capital is on the grids, for any $m \in [1, nN-1]$, we set $n_m = n_{nN} + (nN - m)\log(1-\delta_N)$ where we choose the number of grids nN such that $n_1 < \bar{s}(\mathcal{T}) - 3\sigma_s$. After that, for any $j \in [1, n_s]$, we let $s_j = n_{m'(j)}$ where $m^{'}(1) = 1$, $m^{'}(n_s) = nN$, and $m'(j+1) - m'(j)$ almost has the same distance. In the end, given the grids of s, we calculate the transition matrix $rev^S_{j \to j'}$.

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

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

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

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

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. 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 $\text{DH}_k^{\max}$ and $\text{DH}_p^{\max}$ denote the Den Haan statistics for aggregate capital K and price p, respectively, which are maximum absolute log difference between actual simulated (K_t, p_t) and the forecasted (K_t, p_t) using the equilibrium mappings $\hat{\Gamma}_p$ and $\hat{\Gamma}_K$. The forecast mapping converge when

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

where $\epsilon = 1\%$.

Internal accuracy of the approximation This section reports the basic accuracy statistics to evaluate the accuracy of heterogeneous agents models with aggregate uncertainty used in the literature. We show that the R2 implied by the following forecasting regressions for price $\hat{p}_t$ and aggregate capital $\hat{K}_{t+1}$ are close to 1:

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

B.2 Solving the Bellman equation

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

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

$$s.t.\ d_t = rev_t - g_t - h_t - tc_t, \tag{24}$$

$$\text{where } tc_t = \begin{cases} \frac{f_o(\mathcal{F},\mathcal{T})}{S_t} k_t + f_a & \text{if } \phi_t = 1 \\ \\ \frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_n)n_{t-1}} k_t & \text{if } \phi_t = 0 \end{cases}, \tag{25}$$

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

$$h_t = \begin{cases} (S_t - (1-\delta_n) n_{t-1}) \cdot 1_{\{S_t - (1-\delta_n) n_{t-1} > 0\}}, & \text{if } \phi_t = 1 \\ \\ 0, & \text{if } \phi_t = 0 \end{cases}. \tag{27}$$

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

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

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

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

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

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

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

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

$$s.t.\ d_t = rev_t - g_t - h_t - tc_t, \tag{28}$$

$$\text{where } tc_t = \frac{f_o\left(\mathcal{F}, \mathcal{T}\right)}{\left(1-\delta_n\right)n_{t-1}}k_t, \tag{29}$$

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

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

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

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

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

Under the case $\phi_t = 0$, their technology capital depreciates at the rate of δ_n. This implies, if at time $t+1$, the grid of n_t is at n_{m-1}, then the grid of n_{t-1} is at n_m from equation (30). Therefore, numerically we solve the Bellman equation through

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

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

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

$$s.t.\ d_t = rev_t - g_t - h_t - tc_t, , \tag{31}$$

$$\text{where } tc_t = \frac{f_o\left(\mathcal{F}, \mathcal{T}\right)}{S_t} k_t + f_a, \tag{32}$$

$$n_t = S_t, \tag{33}$$

$$h_t = (S_t - (1-\delta_n) n_{t-1}) \cdot 1_{\{S_t - (1-\delta_n) n_{t-1} > 0\}}. \tag{34}$$

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

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

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

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

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.

C Markup decomposition

The dynamic problem in our model setup is given by

$$v_{j,t}(\Theta_t) = \max_{i_{j,t},\phi_{j,t}} : \left\{d_{j,t} + E_t\left[M_{t,t+1}v_{j,t+1}(\Theta_{t+1})\right]\right\}. \tag{35}$$

$$\text{s.t.} \qquad k_{j,t+1} = i_{j,t} + (1-\delta_k)k_{j,t}, \tag{36}$$

$$d_{j,t} = P_t^{1-\frac{\eta}{\xi}}\left(X_t z_{j,t} k_{j,t}\right)^{1-\frac{1}{\xi}} - g_{j,t} - h_{j,t} - oc_{j,t}\left(k_{j,t}\right) - ac_{j,t}. \tag{37}$$

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

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

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

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

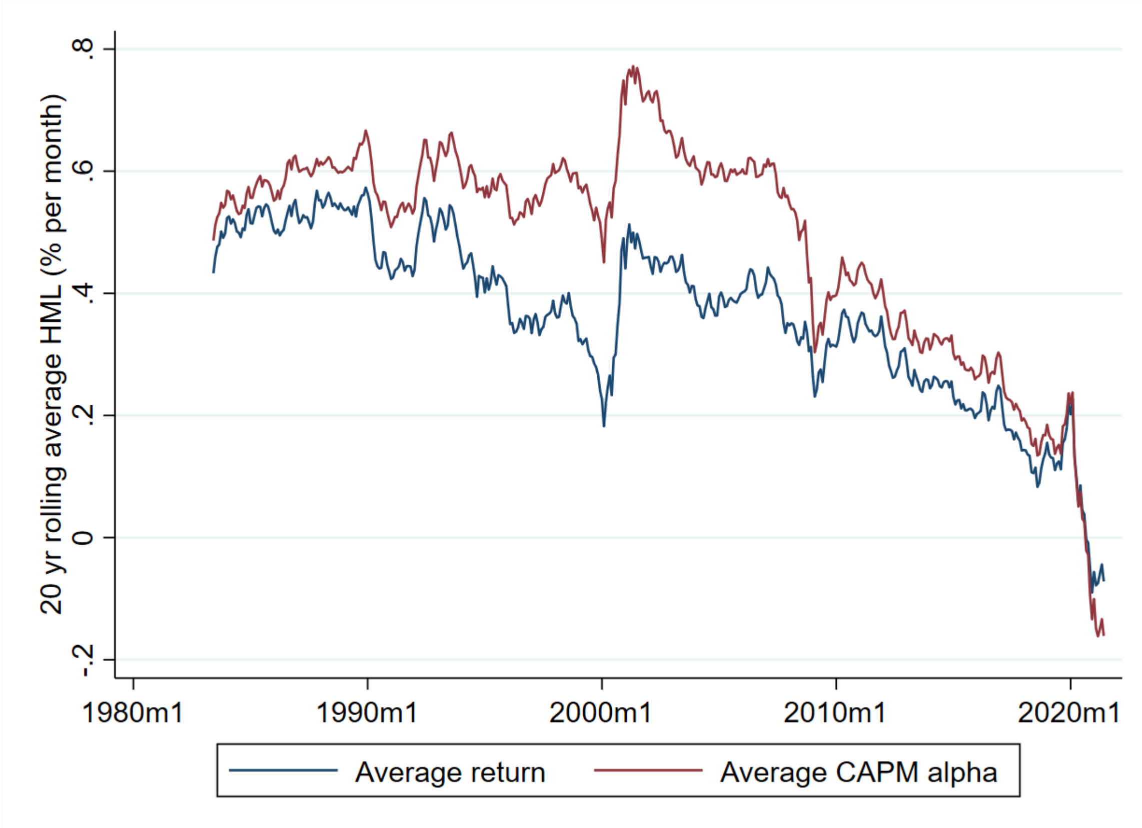
$$\Longrightarrow \left[\frac{P_t^{\xi-\eta}}{y_{j,t}}\right]^{\frac{1}{\xi}} = \left(\frac{\xi}{\xi-1}\right)\left\{\frac{\partial \varkappa_t\left(y_{j,t},\phi_{j,t}\right)}{\partial y_t} + \frac{\partial \varkappa_{j,t}\left(y_{j,t},\phi_{j,t}\right)}{\partial \phi_{j,t}}\frac{\partial \phi_{j,t}}{\partial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

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

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

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

Figure A.1: Rolling average HML factor return



This figure plots the 20-year rolling average monthly return and CAPM alpha of the HML factor. The sample period is from 1963m7 to 2021m6.

Table A.1: Decline of value premium, alternative sample periods

This table estimates the difference in the performance of the HML factor (in columns 1 and 2), the top-minus-bottom BM quintile (in columns 3 and 4), big cap HML factor (in columns 5 and 6), and small cap HML factor (in columns 7 and 8) between two sample periods. Panel A compares the performance before and after 1993m6. Panel B compares the performance before and after 2007m6. Panel C compares the performance before and after 2001m6. The sample starts from 1963m7 in all three panels. The sample sends in 2021m6 in Panel A and B and ends in 2019m12 in Panel C. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HML factor		Top - Bottom		Big HML		Small HML	
Panel A: before and after 1993m6								
After 1993m6	-0.40*	-0.35	-0.52*	-0.53*	-0.48*	-0.47*	-0.33	-0.24
	(-1.81)	(-1.59)	(-1.83)	(-1.83)	(-1.93)	(-1.86)	(-1.31)	(-1.00)
Mkt-RF		-0.14***		0.02		-0.02		-0.25***
		(-3.70)		(0.48)		(-0.35)		(-7.34)
Constant	0.46***	0.52***	0.55***	0.54***	0.38**	0.38**	0.55***	0.66***
	(3.37)	(4.06)	(2.97)	(2.94)	(2.43)	(2.51)	(3.68)	(4.98)
Observations	696	696	696	696	696	696	696	696
Adjusted R^2	0.003	0.045	0.003	0.003	0.004	0.003	0.001	0.122
Panel B: before and after 2007m6								
After 2007m6	-0.79***	-0.73**	-0.85**	-0.86**	-0.72**	-0.71**	-0.85***	-0.75**
	(-2.91)	(-2.55)	(-2.27)	(-2.29)	(-2.21)	(-2.15)	(-3.04)	(-2.54)
Mkt-RF		-0.13***		0.02		-0.01		-0.25***
		(-3.73)		(0.51)		(-0.34)		(-7.41)
Constant	0.46***	0.52***	0.51***	0.49***	0.32**	0.33**	0.60***	0.72***
	(3.75)	(4.56)	(3.41)	(3.31)	(2.43)	(2.48)	(4.23)	(5.76)
Observations	696	696	696	696	696	696	696	696
Adjusted R^2	0.012	0.053	0.008	0.008	0.008	0.006	0.011	0.130
Panel C: before and after 2001m6, exclude 2020 and 2021								
After 2001m6	-0.44**	-0.42*	-0.49*	-0.49*	-0.49*	-0.48*	-0.39	-0.36
	(-2.01)	(-1.88)	(-1.67)	(-1.66)	(-1.91)	(-1.86)	(-1.59)	(-1.50)
Mkt-RF		-0.16***		-0.01		-0.04		-0.27***
		(-4.71)		(-0.23)		(-1.06)		(-8.31)
Constant	0.45***	0.52***	0.48***	0.48***	0.33**	0.35**	0.56***	0.70***
	(3.26)	(4.16)	(2.91)	(2.96)	(2.28)	(2.47)	(3.64)	(5.14)
Observations	678	678	678	678	678	678	678	678
Adjusted R^2	0.004	0.064	0.003	0.001	0.004	0.006	0.002	0.144

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

This table reports the performance intra-industry value premium. Specifically, we measure value premium (the difference in return between stocks in the top and bottom book-to-market quintile) within in each Fama-French 30 industry and average across industries to compute the intra-industry value premium. We use the total industry market cap as weights to average each industry's value premium. Columns 1 and 4 reports the average value premium and the CAPM alpha of value premium before 2001m6. Columns 2 and 5 reports after 2001m6. Columns 3 and 6 estimates the difference in value premium between the two sub-periods. The full sample ends in 2021m6. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

VARIABLES	(1) Before	(2) After	(3) Full sample	(4) Before	(5) After	(6) Full sample
After 2001m6			-0.49*			-0.50*
			(-1.70)			(-1.75)
MKT				-0.07	0.30***	0.05
				(-1.24)	(4.31)	(1.17)
Constant	0.71***	0.21	0.71***	0.74***	-0.01	0.68***
	(4.48)	(0.88)	(4.48)	(4.79)	(-0.02)	(4.31)
Observations	456	240	696	456	240	696
Adjusted R^2	0.000	0.000	0.003	0.007	0.120	0.006

Table A.3: Average markup and change in markup by industry

This table reports the average markup in Fama-French 30 industries (excluding utilities and financial industries). Panel A lists average markup in each industry. Panel B regresses change in markup on the average markup before 2000. We measure markup as the ratio between total sales and cost of goods sold.

	Average markup			
Industry	1962-2000	2001-2020	Change	% Change
Healthcare	1.87	2.52	0.65	35%
Personal and Business Services	2.29	2.86	0.58	25%
Printing and Publishing	1.89	2.33	0.44	23%
Apparel	1.44	1.82	0.39	27%
Business Equipment	1.78	2.16	0.38	21%
Beer & Liquor	1.70	2.07	0.38	22%
Tobacco Products	1.78	2.12	0.34	19%
Everything Else	1.48	1.78	0.30	20%
Communication	1.94	2.22	0.29	15%
Consumer Goods	1.76	2.02	0.26	15%
Petroleum and Natural Gas	2.27	2.51	0.24	10%
Recreation	1.84	2.07	0.23	13%
Chemicals	1.57	1.78	0.22	14%
Food Products	1.47	1.66	0.19	13%
Retail	1.56	1.69	0.14	9%
Transportation	1.35	1.47	0.13	10%
Textiles	1.31	1.43	0.12	9%
Aircraft, ships, and railroad equipment	1.31	1.40	0.09	7%
Wholesale	1.47	1.55	0.08	5%
Restaurants, Hotels, Motels	1.46	1.53	0.07	5%
Fabricated Products and Machinery	1.50	1.57	0.07	5%
Metal Mining	1.55	1.57	0.02	1%
Construction	1.38	1.38	-0.01	-1%
Automobiles and Trucks	1.33	1.32	-0.01	-1%
Steel Works Etc	1.28	1.26	-0.02	-1%
Electrical Equipment	1.67	1.65	-0.02	-1%
Coal	1.30	1.25	-0.05	-4%
Business Supplies and Shipping	1.45	1.39	-0.05	-4%

Table A.4: Change in markup by industry and industry markup before 2000

This table regresses change in markup on the average markup before 2000. We measure markup as the ratio between total sales and cost of goods sold.

VARIABLES	(1) change in markup	(2) % change in markup
Avg. markup before 2000	0.47***	0.21***
	(4.78)	(3.41)
Constant	-0.56***	-0.22**
	(-3.50)	(-2.24)
Observations	28	28
Adjusted R-squared	0.447	0.282

Table A.5: Excess return and CAPM alpha of BM and industry-markup sorted portfolios

This table reports the average return and CAPM alpha of double sorted portfolios in different sample periods. We sort SIC 4-digit industries into terciles based on each industry's markup and pool firms together in each tercile We also sort based on their book-to-market ratio into quntiles independently. We use NYSE cut-offs to create portfolios. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	Lo BM	**2**	**3**	**4**	**Hi BM**	**Hi-Lo**
Panel A: average return from 1963m7 to 2001m6						
Low Markup	0.16	0.29	0.53**	0.59**	0.74***	0.59***
	(0.51)	(1.16)	(2.25)	(2.44)	(2.91)	(2.65)
Mid markup	0.33	0.45*	0.56**	0.77***	1.01***	0.68***
	(1.13)	(1.76)	(2.24)	(3.14)	(3.83)	(2.98)
High Markup	0.54**	0.59**	0.86***	0.73***	1.34***	0.80***
	(2.20)	(2.46)	(3.73)	(2.91)	(4.68)	(3.58)
High - Low	0.38**	0.30*	0.33	0.13	0.60***	0.21
	(2.10)	(1.67)	(1.62)	(0.61)	(3.01)	(0.84)
Panel B: average return from 2001m7 to 2021m6						
Low Markup	0.20	0.67**	0.55	0.77*	0.95*	0.75**
	(0.56)	(2.48)	(1.49)	(1.92)	(1.86)	(2.09)
Mid markup	0.94***	0.93***	0.94**	0.84**	0.75	-0.18
	(2.69)	(2.80)	(2.46)	(2.06)	(1.48)	(-0.49)
High Markup	0.94***	0.77**	0.71**	0.59*	0.71*	-0.23
	(3.27)	(2.44)	(2.15)	(1.68)	(1.69)	(-0.76)
High - Low	0.74***	0.09	0.15	-0.18	-0.24	-0.98**
	(3.05)	(0.39)	(0.57)	(-0.63)	(-0.65)	(-2.58)
Panel C: average CAPM alpha from 1963m7 to 2001m6						
Low Markup	-0.48***	-0.21	0.07	0.11	0.25*	0.72***
	(-3.16)	(-1.55)	(0.53)	(0.80)	(1.65)	(3.32)
Mid markup	-0.30**	-0.10	0.03	0.29**	0.51***	0.81***
	(-2.30)	(-0.86)	(0.25)	(2.10)	(3.21)	(3.72)
High Markup	0.01	0.07	0.42***	0.27*	0.80***	0.79***
	(0.08)	(0.66)	(3.00)	(1.71)	(4.58)	(3.54)
High - Low	0.49***	0.28	0.34*	0.17	0.55***	0.06
	(2.73)	(1.58)	(1.67)	(0.76)	(2.77)	(0.25)
Panel D: average CAPM alpha from 2001m7 to 2021m6						
Low Markup	-0.60***	0.10	-0.29*	-0.12	-0.14	0.47
	(-2.85)	(0.64)	(-1.66)	(-0.58)	(-0.47)	(1.37)
Mid markup	0.15	0.18	0.05	-0.05	-0.28	-0.43
	(0.87)	(1.13)	(0.29)	(-0.25)	(-0.86)	(-1.13)
High Markup	0.28**	0.06	-0.01	-0.17	-0.14	-0.42
	(2.12)	(0.37)	(-0.04)	(-0.85)	(-0.54)	(-1.39)
High - Low	0.88***	-0.05	0.29	-0.05	-0.01	-0.89**
	(3.37)	(-0.21)	(1.08)	(-0.18)	(-0.02)	(-2.18)

Table A.6: Double sort by BM and alternative measures of markup

This table reports the average return and CAPM alpha of stocks sorted by book-to-market ratio and alternative measures markup. The alternative measure of markup is based on De Loecker, Eeckhout, and Unger (2020), which equals to $\theta \times \frac{COGS}{Sale}$, where Îž is industry level output elasticity to cost. Panel A and B report average return before and after 2001m6. Panel C and D report average CAPM alpha before and after 2001m6. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	Lo BM	2	3	4	Hi BM	Hi-Lo
Panel A: average return 1963m7 to 2001m6						
Lo markup	0.38	0.45*	0.62**	0.73***	0.69***	0.31
	(1.32)	(1.80)	(2.59)	(2.96)	(2.67)	(1.53)
Mid	0.25	0.50**	0.52**	0.73***	0.89***	0.65***
	(0.90)	(2.04)	(2.33)	(3.26)	(3.46)	(3.31)
Hi markup	0.53**	0.63***	0.63***	0.82***	1.21***	0.68***
	(2.22)	(2.85)	(2.93)	(3.43)	(4.13)	(2.98)
Hi - Lo	0.15	0.18	0.01	0.09	0.52***	0.37
	(0.92)	(1.29)	(0.04)	(0.49)	(2.82)	(1.60)
Panel B: average return 2001m7 to 2021m6						
Lo markup	0.59*	0.72***	0.79**	0.77**	1.08**	0.48
	(1.79)	(2.72)	(2.33)	(2.00)	(2.33)	(1.56)
Mid	1.20***	0.88***	0.91**	0.71*	0.81*	-0.38
	(3.39)	(2.85)	(2.49)	(1.90)	(1.68)	(-1.09)
Hi markup	0.78***	0.81***	0.72**	0.66*	0.61	-0.18
	(2.83)	(2.61)	(2.22)	(1.83)	(1.44)	(-0.60)
Hi - Lo	0.19	0.08	-0.08	-0.11	-0.47	-0.66**
	(1.05)	(0.41)	(-0.39)	(-0.53)	(-1.53)	(-2.01)
Panel C: CAPM alpha 1963m7 to 2001m6						
Lo markup	-0.23*	-0.08	0.13	0.22*	0.17	0.40**
	(-1.79)	(-0.63)	(1.04)	(1.76)	(1.20)	(2.10)
Mid	-0.36***	-0.04	0.05	0.28**	0.39***	0.75***
	(-3.33)	(-0.47)	(0.48)	(2.28)	(2.65)	(4.01)
Hi markup	0.01	0.14	0.19	0.36**	0.67***	0.66***
	(0.10)	(1.63)	(1.64)	(2.55)	(3.63)	(2.88)
Hi - Lo	0.24	0.22	0.06	0.14	0.50***	0.25
	(1.58)	(1.53)	(0.36)	(0.76)	(2.70)	(1.12)
Panel D: CAPM alpha 2001m7 to 2021m6						
Lo markup	-0.17	0.14	0.00	-0.09	0.07	0.24
	(-1.10)	(0.98)	(0.03)	(-0.49)	(0.28)	(0.81)
Mid	0.40**	0.19	0.03	-0.17	-0.23	-0.63*
	(2.23)	(1.23)	(0.24)	(-1.08)	(-0.86)	(-1.73)
Hi markup	0.12	0.09	-0.03	-0.15	-0.26	-0.37
	(1.14)	(0.66)	(-0.18)	(-0.83)	(-0.99)	(-1.29)
Hi - Lo	0.29	-0.06	-0.03	-0.06	-0.33	-0.62*
	(1.55)	(-0.30)	(-0.15)	(-0.26)	(-1.01)	(-1.76)

Table A.7: Double sort by BM and operating leverage

This table reports the average return and CAPM alpha of stocks sorted by book-to-market ratio and operating leverage. We measure operating leverage as $\frac{(COGS+SG\&A)}{Asset}$. Panel A and B report average return before and after 2001m6. Panel C and D report average CAPM alpha before and after 2001m6. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: average return 1963m7 to 2001m6						
	Lo BM	**2**	**3**	**4**	**Hi BM**	**Hi-Lo**
Lo operating leverage	0.46*	0.54**	0.48**	0.68***	0.93***	0.48**
	(1.84)	(2.34)	(2.16)	(2.86)	(3.46)	(2.16)
Mid	0.41*	0.59**	0.68***	0.78***	0.83***	0.43**
	(1.70)	(2.43)	(2.91)	(3.15)	(3.22)	(2.12)
Hi operating leverage	0.58**	0.61**	0.72***	0.78***	0.97***	0.39*
	(2.16)	(2.53)	(3.04)	(3.14)	(3.56)	(1.87)
Hi - Lo	0.12	0.07	0.24	0.10	0.03	-0.09
	(0.85)	(0.43)	(1.44)	(0.59)	(0.19)	(-0.42)
Panel B: average return 2001m7 to 2021m6						
Lo operating leverage	0.78***	0.78**	0.63*	0.61*	0.52	-0.25
	(2.63)	(2.56)	(1.91)	(1.66)	(1.20)	(-0.84)
Mid	0.90***	0.94***	0.95**	0.71*	1.45***	0.55*
	(3.12)	(2.83)	(2.47)	(1.75)	(3.16)	(1.74)
Hi operating leverage	0.89***	0.82***	0.85**	0.95**	1.33***	0.44
	(2.71)	(3.09)	(2.52)	(2.42)	(2.72)	(1.17)
Hi - Lo	0.12	0.04	0.22	0.35*	0.81**	0.69**
	(0.64)	(0.17)	(1.16)	(1.69)	(2.47)	(2.00)
Panel C: CAPM alpha 1963m7 to 2001m6						
Lo operating leverage	-0.08	0.03	0.02	0.19	0.41***	0.49**
	(-0.74)	(0.32)	(0.15)	(1.58)	(2.63)	(2.24)
Mid	-0.12	0.07	0.19*	0.27**	0.33**	0.45**
	(-1.26)	(0.61)	(1.66)	(2.07)	(2.20)	(2.24)
Hi operating leverage	-0.00	0.10	0.23*	0.29**	0.47***	0.47**
	(-0.03)	(0.89)	(1.90)	(2.08)	(2.73)	(2.37)
Hi - Lo	0.08	0.07	0.22	0.10	0.06	-0.02
	(0.53)	(0.44)	(1.29)	(0.59)	(0.34)	(-0.08)
Panel D: CAPM alpha 2001m7 to 2021m6						
Lo operating leverage	0.08	0.07	-0.14	-0.23	-0.41*	-0.48
	(0.63)	(0.53)	(-0.94)	(-1.37)	(-1.66)	(-1.64)
Mid	0.21*	0.16	0.03	-0.21	0.47*	0.26
	(1.95)	(1.17)	(0.23)	(-1.05)	(1.80)	(0.85)
Hi operating leverage	0.15	0.26*	0.09	0.08	0.35	0.19
	(0.94)	(1.67)	(0.52)	(0.37)	(1.13)	(0.53)
Hi - Lo	0.08	0.19	0.23	0.31	0.75**	0.68*
	(0.43)	(0.94)	(1.16)	(1.46)	(2.22)	(1.90)

Table A.8: Value premium in low, mid, and high-markup firms (drop micro cap)

This table reports the value premium among low-markup firms (in columns 1 and 5), mid-markup firms (in columns 2 and 6), and high-markup firms (in columns 3 and 7) in different sample periods. Columns 4 and 8 report the difference in value premium between high- and low-markup firms. We sort companies into terciles based on their markup and into quintiles based on their book-to-market ratio. We use NYSE cut-offs. We compute value premium in each markup tercile as the value-weighted return of top book-to-market firms minus the value-weighted return of bottom book-to-market firms in the tercile. We exclude micro-cap stocks (i.e., bottom NYSE size quintile) from the calculation of value premium. Panel A reports the performance from 1963m7 to 2001m6. Panel B reports the performance from 2001m7 to 2021m6. Panel C uses all sample period from 1963m7 to 2021m6 with a dummy variable that indicates if a month is after 2001m6. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	Mid	High	High-Low	Low	Mid	High	High-Low
				Panel A: 1963m7 to 2001m6				
Mkt-RF					-0.21***	-0.20***	0.03	0.24***
					(-3.25)	(-3.08)	(0.43)	(4.24)
Constant	0.36*	0.75***	0.71***	0.35	0.47**	0.86***	0.69***	0.23
	(1.72)	(3.72)	(3.15)	(1.45)	(2.30)	(4.39)	(3.08)	(0.97)
Observations	456	456	456	456	456	456	456	456
Adjusted R^2	0.000	0.000	0.000	0.000	0.041	0.042	-0.001	0.041
				Panel B: 2001m7 to 2021m6				
Mkt-RF					0.33***	0.26***	0.32***	-0.01
					(4.29)	(2.70)	(3.45)	(-0.10)
Constant	0.57*	-0.33	-0.32	-0.88**	0.32	-0.52	-0.55*	-0.87**
	(1.84)	(-0.92)	(-0.98)	(-2.57)	(1.07)	(-1.39)	(-1.75)	(-2.35)
Observations	240	240	240	240	240	240	240	240
Adjusted R^2	0.000	0.000	0.000	0.000	0.090	0.038	0.074	-0.004
				Panel C: 1963m7 to 2021m6				
After 2001m6	0.20	-1.08***	-1.03***	-1.23***	0.21	-1.07***	-1.06***	-1.27***
	(0.55)	(-2.64)	(-2.60)	(-2.93)	(0.56)	(-2.58)	(-2.71)	(-3.00)
Mkt-RF					-0.03	-0.05	0.13**	0.15***
					(-0.49)	(-0.83)	(2.25)	(2.87)
Constant	0.36*	0.75***	0.71***	0.35	0.37*	0.78***	0.65***	0.27
	(1.72)	(3.72)	(3.14)	(1.45)	(1.81)	(3.92)	(2.85)	(1.15)
Observations	696	696	696	696	696	696	696	696
Adjusted R^2	-0.001	0.010	0.008	0.011	-0.002	0.011	0.020	0.027

Table A.9: Value premium in low, mid, and high-markup industries (drop micro cap)

This table reports the value premium among low-markup industries (in columns 1 and 5), mid-markup industries (in columns 2 and 6), and high-markup industries (in columns 3 and 7) in different sample periods. Columns 4 and 8 report the difference in value premium between high- and low-markup industries. We sort companies into terciles based on their industry markup and into quintiles based on their book-to-market ratio. We define industries based on SIC 4-digit codes and require an industry-year to have at least 5 different companies. We compute value premium in each markup tercile as the value-weighted return of top book-to-market firms minus the value-weighted return of bottom book-to-market firms in the tercile. Panel A reports the performance from 1963m7 to 2001m6. Panel B reports the performance from 2001m7 to 2021m6. Panel C uses all sample period from 1963m7 to 2021m6 with a dummy variable that indicates if a month is after 2001m6. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	Mid	High	High-Low	Low	Mid	High	High-Low
				Panel A: 1963m7 to 2001m6				
Mkt-RF					-0.27***	-0.24***	0.03	0.30***
					(-3.72)	(-3.26)	(0.40)	(3.67)
Constant	0.54**	0.62**	0.75***	0.21	0.68***	0.74***	0.73***	0.06
	(2.37)	(2.58)	(3.17)	(0.75)	(3.01)	(3.23)	(3.11)	(0.21)
Observations	456	456	456	456	456	456	456	456
Adjusted R^2	0.000	0.000	0.000	0.000	0.059	0.042	-0.002	0.049
				Panel B: 2001m7 to 2021m6				
Mkt-RF					0.37***	0.32***	0.24***	-0.13
					(4.10)	(2.66)	(3.05)	(-1.05)
Constant	0.69*	-0.23	-0.31	-1.00**	0.42	-0.47	-0.49	-0.91**
	(1.91)	(-0.61)	(-0.99)	(-2.52)	(1.21)	(-1.22)	(-1.57)	(-2.13)
Observations	240	240	240	240	240	240	240	240
Adjusted R^2	0.000	0.000	0.000	0.000	0.082	0.055	0.044	0.004
				Panel C: 1963m7 to 2021m6				
After 2001m6	0.15	-0.85*	-1.06***	-1.21**	0.16	-0.84*	-1.08***	-1.25**
	(0.36)	(-1.90)	(-2.69)	(-2.50)	(0.38)	(-1.86)	(-2.77)	(-2.56)
Mkt-RF					-0.05	-0.05	0.10*	0.15**
					(-0.87)	(-0.73)	(1.79)	(2.29)
Constant	0.54**	0.62**	0.75***	0.21	0.57**	0.64***	0.70***	0.13
	(2.37)	(2.58)	(3.17)	(0.75)	(2.48)	(2.75)	(2.95)	(0.48)
Observations	696	696	696	696	696	696	696	696
Adjusted R^2	-0.001	0.004	0.009	0.008	-0.001	0.004	0.015	0.019

Table A.10: Value premium vs. intangibles

This table reports the value premium in different intangible-sorted-tercile portfolios after 2001m6. We regress the return of high-BM quintile minus low-BM quintile on the market factor to report the CAPM alpha of value premium. Panel A measures intangible by R&D expense to sales. Panel B measures intangible as knowledge capital to asset. Panel C measures intangible as organizational capital to asset. Panel D measures intangible as the sum of knowledge and organizational capital to asset. Knowledge and organization capital are obtained from WRDS Peters and Taylor dataset. Sample period is from 2001m7 to 2021m6. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively

Panel A: sort by R&D to sale				
	Low	Mid	High	High - Low
Value premium	0.14	-0.28	-0.24	-0.38
	(0.42)	(-0.74)	(-0.74)	(-0.88)
Panel B: sort by knowledge capital to asset				
	Low	Mid	High	High - Low
Value premium	-0.06	-0.15	0.20	0.26
	(-0.20)	(-0.39)	(0.62)	(0.70)
Panel C: sort by Organizational capital to asset				
	Low	Mid	High	High - Low
Value premium	-0.22	0.13	-0.11	0.12
	(-0.70)	(0.43)	(-0.26)	(0.26)
Panel D: sort by Intangible capital to asset				
	Low	Mid	High	High - Low
Value premium	-0.28	-0.00	-0.33	-0.04
	(-0.83)	(-0.01)	(-0.98)	(-0.10)

Table A.11: Decline of intangible augmented value premium

This table reports the CAPM alpha of intangible-capital-augmented value premium. In columns 1 to 3, we add different measures of intangible asset to book equity to construct intangible augmented book-to-market. Then we sort firms into quintiles based on this new measure to calculate intangible-augmented value premium. The three types of intangible capital are knowledge capital, organizational capital, and all intangible capital, obtained from Peters and Taylor dataset, to book equity. Column 4 uses the intangible HML factor from Eisfeldt, Kim, and Papanikolaou (2022). Sample period is from 2001m7 to 2021m6. Panel A reports CAPM alpha before 2001m6. Panel B reports after. Panel C uses full sample and estimates the difference between two sub-periods. All t-statistics (in parentheses) are based on (heteroskedasticity) robust standard errors. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	(K_{Know}+BM)/ME	(K_{Org}+BM)/ME	(K_{Intan}+BM)/ME	HML^{INT}
		Panel A: before 2001m6		
MKT	-0.09	-0.11	-0.08	-0.10**
	(-1.21)	(-1.47)	(-1.00)	(-2.24)
Constant	0.78***	0.78***	0.82***	0.68***
	(3.54)	(3.46)	(3.65)	(6.14)
Observations	318	318	318	318
Adjusted R^2	0.007	0.014	0.004	0.047
		Panel B: after 2001m6		
MKT	0.31***	0.35***	0.34***	0.09**
	(4.55)	(4.76)	(4.84)	(2.34)
Constant	-0.01	-0.18	-0.09	0.23
	(-0.06)	(-0.70)	(-0.33)	(1.63)
Observations	240	240	240	240
Adjusted R^2	0.114	0.128	0.120	0.033
		Panel C: full sample 1975 to 2021		
After 2001m6	-0.49	-0.61*	-0.60*	-0.30*
	(-1.48)	(-1.73)	(-1.71)	(-1.74)
MKT	0.08	0.08	0.10*	-0.02
	(1.56)	(1.41)	(1.75)	(-0.61)
Constant	0.65***	0.63***	0.69***	0.61***
	(2.95)	(2.75)	(3.02)	(5.57)
Observations	558	558	558	558
Adjusted R^2	0.009	0.009	0.013	0.004

Table A.12: asset pricing test

This table reports the results of asset pricing tests. We specify the following stochastic discount factor

$$M_t = 1 - b_M \times MKT_t - b_{MG} \times MG_t$$

where MKT_t is market return in time t and MG_t is growth in aggregate markup in time t. We measure MG_t as the difference in growth rate between aggregate sales and aggregate cost-of-goods-sold of all companies in COMPUSTAT (exclude utilities and financials). We use different sets of testing assets to estimate b_M and b_{MG}. Test assets are 3 markup by 5 bm portfolios, 5 size by 5 bm portfolios, 10 investment decile portfolios, and 10 operating profitability decile portfolios.

	Panel A: 1963 to 2020			
	bm x markup		bm x markup, size x bm, inv, op	
b_M	3.02	1.02	2.97	0.68
t	2.98	0.57	2.07	0.33
b_{MG}		0.96		1.11
t		2.06		2.03
MAE	1.84	1.43	2.03	1.61
	Panel B: 1963 to 2000			
	bm x markup		bm x markup, size x bm, inv, op	
b_M	3.14	1.52	3.11	1.59
t	2.31	0.64	1.4	0.62
b_{MG}		1.18		1.09
t		2.32		1.86
MAE	2.88	2.1	2.63	2.24
	Panel C: 2001 to 2020			
	bm x markup		bm x markup, size x bm, inv, op	
b_M	2.81	3.46	2.73	2.07
t	1.82	1.41	1.41	0.76
b_{MG}		-0.21		0.22
t		-0.32		0.33
MAE	1.61	1.66	1.92	1.92