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 important trends during the last few decades: the decline of the value premium and the rise of the markup. We show that the decline of the value premium and the rise of the markup are primarily driven by firms with high markups, whereas the value premium and the markup remain stable in firms with low markups. We develop a dynamic model with stochastic technology frontier and heterogeneity in firms' technology adoption decisions to explain this finding. In the model, by adopting the latest technology firms on the technology frontier reduce the operating costs in production, which in turn increases the markup and decreases the dispersion in their exposures to the aggregate technology frontier shocks. This leads to the rise of the markup and the decline of the value premium among the high markup firms. For firms that cannot catch up with the technology frontier due to adoption costs, they keep operating the old technology, thus the markup stays low and the value premium remains sizable.

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

1 Introduction

Much research documents a decline in the value premium and a rise in the measured markups over the recent decades (e.g., Fama and French 2022; De Loecker, Eeckhout, and Unger 2020). We show that these two trends are closely connected, and provide a unified framework to understand both. Empirically, we find that the decline of the value premium is primarily driven by firms with high markups; furthermore, these firms are also those experiencing large increases in their markups during the last few decades, which drives the aggregate markup to increase. In contrast, in low markup firms, both the value premium and the markup remain unchanged. We develop a dynamic model economy that features a stochastic technological frontier and costly endogenous technology adoptions. We show that the increase in the efficiency of the aggregate technology frontier and the heterogeneity in firms' technology adoption decisions are crucial to generate the joint dynamics of the decline in the value premium and the rise in the markups, and the cross-sectional difference in changes of the value premium and markups.

We start off by documenting a decline of the value premium in the past few decades. Consistent with Fama and French (2022), the spread between high and low book-to-market quintile portfolios decreases significantly from 5.7% in 1963-2001 to -0.4% in 2001-2021. In addition, the CAPM alpha of the value premium also decreases significantly from 6.6% to -3.6%. The decline of the value premium is also robust to alternative measures of the value investing, e.g., the HML factor also experiences a similar decline.

We show that the decline in the value premium is closely related to the rise of the firms' markups. In particular, we find that the decrease of the value premium is primarily driven by the firms with high markups, with the value premium dropping from 9.4% in 1963-2001 to -3% in 2001-2021, while in the low markup firms it remains sizable, with 5.3% in 1963-2001 and 7.3% in 2001-2021. More important, the same group of the high markup firms also experience large increases in markups, while the low markup firms' markups stay unchanged over time. These together imply an increase in the aggregate markup, shedding lights on

De Loecker, Eeckhout, and Unger (2020) who argued that understanding the rise in the aggregate markup is important to understand the market structure change.

To understand the economic driving forces of the empirical results, we develop a stochastic dynamic firm model that features i) an aggregate technology frontier fluctuating over time, which captures the changes in advanced technologies, and ii) costly technology adoption by firms. In the model, firms can advance their technology level by choosing to adopt the latest technology but at the expense of fixed adoption costs. The benefit of adoption is that new technology directly makes firms more efficient in production by reducing the operating cost. This captures the fact that new technologies (ICT technology, cloud storage and computing, automation, AI, etc.,) allow firms to span into multiple product lines or multiple markets, which reduces the marginal cost in production as the new technologies are non-rival and scalable (Aghion et al 2020, Hsieh and Rossi-Hansberg 2020). As a result, firms that adopt frontier technology have an increase in the markup due to lower marginal cost of production. Furthermore, a lower operating cost also implies lower operating leverage and hence lower exposures to the aggregate technology frontier shocks.

There are also several heterogeneities in the model. First there is a cross-time heterogeneity in the efficiency of the new technology which captures the drastic advancement in the aggregate technology since late 1990s. Second there is a cross-group heterogeneity in the marginal production cost which captures different adoption benefits for firms. Lastly, the within-group heterogeneity in firm-specific productivity generates firm level dispersion in risk. We identify these heterogeneities by using both asset pricing and quantity moments across firms and over time.

We first calibrate the model to the pre-2000 economy and show that the model generates a sizable 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 due to the adoption cost. As a result, they suffer more when the aggregate technology frontier fluctuates over time and hence are riskier. Furthermore, the model also generates sizable CAPM alphas which is consistent with the failure of the CAPM in capturing the value premium in the data. Intuitively, the aggregate technological frontier shock primarily drives the cross-sectional risk dispersion, while the market is more driven by the aggregate productivity shock, and hence the CAPM does not capture the cross-sectional variations in the book-to-market portfolios.

To capture the difference between the before- and after-2000 economies in the aggregate technology, we focus on the increase in the efficiency of the aggregate technology frontier, e.g., the advancements in information and communication technologies, artificial intelligence and machine learning, smarter devices, etc., which affect all firms. However, firms differ in the benefit of the technology adoption, which in the model is inversely related to the marginal cost of production. We show that firms with higher technology adoption benefit choose to adopt the frontier technology, moreover they are also the firms that increase the markups significantly because the marginal operating costs decrease more for them. This in turn drives the aggregate markup to rise. Due to the decrease in the operating costs (operating leverage) for all high markup firms, the dispersion in risk shrinks, which leads to a decline in the value premium.

Contrary to the adopting firms, firms with lower technology adoption benefit do not catch up with the technology frontier. Therefore, they still operate with the old technology and incur large operating costs as a result. Moreover, these non-adopting firms are also those with markups staying low, as the marginal costs of production is high for them. This in turn implies that the dispersion of the exposure to the aggregate frontier shock among the low markup firms remains large as the operating leverage effect is still strong. Hence there still is a sizable value premium in the low markup firms. Taken together, we show that the increase in the efficiency of the aggregate technology frontier and the heterogeneity in technology adoption benefit are quantitatively important to capture the decline of the value premium and the rise of the markup, both of which are primarily driven by the high markup firms.

2 Literature review

This paper relates to several strands of literature. First it is related to the recent literature on the decline of the value premium. Fama and French (2021) document a substantial decline in the value premium in the post-1991 sample period. Several papers attribute the decrease in the value premium to the fact that the book equity of the firm usually does not include intangible assets, e.g., Park, (2019), Arnott et al. (2021), Eisfeldt, Kim, Papanikolaou (2022), and Gulen et al (2022). They propose to add the value of intangible assets to the book value of a firm when computing book-to-market ratios and demonstrate that sorting on this augmented book-to-market ratios enhances the performance of value investing. Unlike these papers, we show that the decline in the value premium is primarily driven by the high markup firms and we quantify this channel is an equilibrium model with technology adoptions.

Our paper also contributes to the theoretical literature that links technology changes to the macroeconomy and financial markets. Papanikolaou (2011), Kogan and Papanikolaou (2014), and Garlappi and Song (2017) study the asset pricing implications of investment-specific technological shocks. We differ in that our model follows the large literature that studies the impact of the changes in aggregate technology frontier, e.g., Parente and Prescott (1994), Greenwood and Yorukoglu (1997), Cooper, Haltiwanger, and Power (1999), Lin, Palazzo and Yang (2019), etc., which allows endogenous technology adoption and investment decisions and 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 (2019) who estimate the price of risk of technology frontier shocks and obtain a positive and significant value.

Our paper closely relates to the literature situated at the intersection of IO and finance, especially how market power affects macroeconomic dynamics and asset prices. Loecker et al. 2019 document the risk of market power from the year 1980 and find significant macroeconomic implications. Recent studies have emerged on the interaction of competition, asset pricing, and industry dynamics (e.g., Hou and Robinson 2005; Novy-Marx, 2007; Carlin, 2009; Aguerrevere, 2009; Carlson et al., 2014; Opp et al., 2014; Bustamante, 2015; Koijen and Yogo, 2015; Bustamante and Donangelo, 2017; Corhay, 2017; Andrei and Carlin, 2018; Chen et al., 2019; Corhay et al., 2020; Dou et al., 2020a; Dou et al., 2021a). Our work differs from this literature in two significant aspects. First, our paper links the trends of markup and cross-sectional returns in the model to address the empirical findings, which has yet to be studied in the previous literature. Second, instead of explicitly modeling industry structure, we focus on the implications of the firms' decisions in adopting the technology frontier for asset prices and markups.

More broadly, our paper relates to the literature on production-based asset pricing. Starting with Gomes et al. (2003), Carlson et al. (2005), Zhang (2005), and Belo, Lin, and Bazdresch(2014), Favilukis and Lin (2016), etc., researchers have been investigating the capabilities of production-based asset pricing models to explain several puzzling features of stock returns in the cross-section of firms. Kogan and Papanikolaou (2012) provide a comprehensive survey of this literature. Through the vanishing of the value premium, our paper reexamines the economic mechanisms for the cross-sectional return spread, which has not been studied in previous literature.

The paper proceeds as follows. Section 3 shows the empirical links between the trend of markup and the trend stock returns in the cross section. Section 4 presents an investment-based asset pricing model with endogenous technology adoption that we use to understand the empirical evidence. Section 5 calibrates and solves the model numerically. Section 6 reports the fit of the model on the cross section of stock returns. Section 7 provides a detailed analysis of the economic mechanisms driving the results. Finally, Section 8 concludes. A separate appendix with additional results and robustness checks is posted online.

3 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.

3.1 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.

3.2 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.

3.3 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.

3.4 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.4 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.4 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.4 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.

3.5 Robustness checks and additional analysis

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.

Our second 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.2 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.3. 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.

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.4, A.5, and A.6. 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.

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.7, where we sort stocks based on firm-level markups, and in Table A.8, 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.

We examine the relationship between value premium and intangible assets. We do not find supporting evidence that the decline of value premium is related to the rise of intangible assets in the economy, another major macroeconomic trend. Specifically, we first show whether firms with different amount of intangibel assets have different degress of decline in value premium. 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.9 presents the result of this exercise. In another 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 after 2001 and find that even with the new book-to-market ratio, value premium is insignificant as shown in Table A.10. This shows that the mismeasurement problem cannot the sole reason of the decline of value premium.

4 Model

In this section, we present a dynamic firm model with a stochastic technology frontier and costly technology adoption to understand the economic mechanism underlying the empirical findings. There are three sources of heterogeneities in the model: the first is the cross-time difference in the efficiency of the aggregate technology frontier, the second is the difference in the benefit of frontier technology adoption 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 late 1990s, this includes the wide use of information technology, artificial intelligence, automation, etc., which significantly improves the production efficiency (Aghion, et al 2020; Hsieh and Rossi-Hansberg, 2020). The cross-group heterogeneity captures the fact that firms have different adoption benefits which can be due to the heterogeneity of the matching between new technology and organization. The firm-specific productivity generates firm-level heterogeneity. We identify the cross-time and cross-firm heterogeneities by using both asset pricing and quantity moments across firms and over time.

4.1 Production technology

Firms use physical capital ($K_{j,t}$) to produce a single final good ($Y_{j,t}$). To save on notation, we omit firm index j whenever possible. The production function is given by

$$Y_t = Z_t X_t K_t,$$

where X_t is aggregate productivity and Z_t is firm-specific productivity. The production function exhibits constant returns to scale. Aggregate productivity follows an AR(1) process

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

in which $x_{t+1} = \log(X_{t+1})$, ε^x_{t+1} is an i.i.d. standard normal shock, and ρ_x and σ_x are the autocorrelation and conditional volatility of aggregate productivity, respectively. Firm-specific productivity also follows the AR(1) process

$$z_{t+1} = \bar{z}(1-\rho_z) + \rho_z z_t + \sigma_z \varepsilon^z_{t+1}, \tag{2}$$

in which $z_{t+1} = \log(Z_{t+1})$, ε^z_{t+1} is an i.i.d. standard normal shock that is uncorrelated across all firms in the economy and independent of ε^x_{t+1}, and $\bar{z}$, ρ_z, and σ_z are the mean, autocorrelation, and conditional volatility of firm-specific productivity, respectively.

As in Bloom (2009), each firm faces an isoelastic demand curve with elasticity ξ:

$$Q_t = BP_t^{-\xi}, \tag{3}$$

where B is a constant demand shifter. These can be combined into a revenue function

$$R\left(B, X_t, Z_t, K_t\right) = Q_t P_t = B^{\frac{1}{\varepsilon}} Q_t^{1-\frac{1}{\varepsilon}} = B^{\frac{1}{\varepsilon}} \left(Z_t X_t K_t\right)^{1-\frac{1}{\varepsilon}}. \tag{4}$$

Physical capital accumulation is given by

$$K_{t+1} = \left(1-\delta_K\right) K_t + I_t, \tag{5}$$

where I_t represents investment and δ_K denotes the capital depreciation rate.

We assume that capital investment entails convex asymmetric adjustment costs, denoted as $G\left(I_t, K_t\right)$, which are given by:

$$G\left(I_t, K_t\right) = \frac{c_K}{2}\left(\frac{I_t}{K_t} - \delta_K\right)^2 K_t, \tag{6}$$

where c_K determined the speed of adjustment. The capital adjustment costs include planning and installation costs, learning the use of new equipment, or the fact that production is temporarily interrupted. For example, a factory may need to close for a few days while a capital refit is occurring.

4.2 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 evolves stochastically, denoted by S_t. It captures new production technologies which generates productivity gains including the information, communication and telecommunication (ICT) technology, cloud storage and computing, automation, the new management practice that improves the efficiency of firms, etc. We assume that the stochastic technology frontier S_{t+1} follows the process below:

$$s_{t+1} = \left(1 - \rho_s\right)\bar{s}\left(\mathcal{T}\right) + \rho_s s_t + \sigma_s \varepsilon^s_{t+1}, \tag{7}$$

in which $s_{t+1} = \log\left(S_{t+1}\right)$, 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. $\bar{s}\left(\mathcal{T}\right)$ 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 and idiosyncratic productivities, firms can advance their technology level by choosing to adopt the latest technology, which determines their firm-specific technology capital N_t. Firms technology capital N_t directly makes firms more efficient in production by reducing the operating costs.

We assume that all firms have access to the aggregate technology frontier S_t. If firms adopt the frontier technology, their technology capital upgrades to S_t. If firms choose not to adopt, then their technology capital depreciates at the rate of δ_N. Let $\phi_t = 1$ denote adoption and $\phi_t = 0$ denote not adoption, firms' technology capital N_t evolves as the following:

$$N_t = \begin{cases} S_t, & \text{if } \phi_t = 1 \\ (1-\delta_N)N_{t-1}, & \text{if } \phi_t = 0 \end{cases}. \tag{8}$$

Accordingly, firms' technology capital investment H_t follows

$$H_t = \begin{cases} S_t - (1-\delta_N)N_{t-1}, & \text{if } \phi_t = 1 \\ 0, & \text{if } \phi_t = 0 \end{cases}. \tag{9}$$

Technology adoption is costly. To adopt the latest frontier technology S_t, firms need to pay a fixed cost of f_a. Therefore the adoption costs AC_t is

$$AC_t = \begin{cases} f_a, & \text{if } \phi_t = 1 \\ 0, & \text{if } \phi_t = 0 \end{cases}. \tag{10}$$

The benefit of adopting the frontier technology is that firms are more efficient with lower operating costs which is given by $\frac{f_o(\mathcal{F},\mathcal{T})}{S_t}K_t$ with $f_o(\mathcal{F},\mathcal{T}) > 0$, where $\mathcal{F}$ denotes the adoption cost heterogeneity across groups.[1] This implies that adoption costs vary both across time and 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 $\frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_N)N_{t-1}}K_t$. Hence the operating

[1] We assume the heterogeneity in operating costs to capture different markups across firms. This is motivated by the empirical findings that there is significant heterogeneity in the change of markups across firms for the last two decades. In particular, the rise of markups is primarily driven by high markup firms as shown in Figure 3.

costs OC_t is given by

$$OC_t = \begin{cases} \frac{f_o(\mathcal{F},\mathcal{T})}{S_t} K_t, & \text{if } \phi_t = 1 \\ \frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_N)N_{t-1}} K_t, & \text{if } \phi_t = 0 \end{cases}. \tag{11}$$

This assumption captures several channels for how new technology make firms more efficient by reducing the costs. First, the IT wave in 1995-2005 allows firms to span into a multiple product lines, e.g., companies take the advantages in cloud storage and computing to reduce the overhead costs associated with spanning multiple markets (Aghion et al (2020)). Second, new technologies, especially software, reduce the marginal cost in production because they are non-rival and scalable, which allows firms to scale up without incurring additional costs (De Ridder (2021)). Similarly, ICT-technology and new management practices allow firms to scale up to expand into multiple locations at a lower cost, which takes places in many sectors especially in the service, retail and wholesale sectors (Hsieh and Rossi-Hansberg (2020)).

To sum up, the total costs TC_t for firms are

$$TC_t = AC_t + OC_t = \begin{cases} \frac{f_o(\mathcal{F},\mathcal{T})}{S_t} K_t + f_a, & \text{if } \phi_t = 1 \\ \frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_N)N_{t-1}} K_t, & \text{if } \phi_t = 0 \end{cases}. \tag{12}$$

4.3 Firms' maximization problem

Finally, firms' dividend D_t is given by

$$D_t = B^{\frac{1}{\varepsilon}} \left(Z_t X_t K_t\right)^{1-\frac{1}{\varepsilon}} - I_t - G\left(I_t, K_t\right) - H_t - TC_t. \tag{13}$$

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

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

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

Define the vector of stat variables as $\Theta_t = (K_t, N_{t-1}, X_t, S_t, Z_t)$, and let $V_t(\Theta_t)$ be the cum-dividend market value of the firm in period t. The firm makes investments I_t and adoption ϕ_t decisions to maximize its cum-dividend market value by solving the problem

$$V_t(\Theta_t) = \max_{I_t,\,\phi_t} : \{D_t + E[M_{t,t+1}V_{t+1}(\Theta_{t+1})]\}. \tag{15}$$

subject to the capital accumulation equation (5) and the flow of funds constraint (13) for all dates t.

4.4 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 (15) at the optimum and obtain

$$V_t(\Theta_t) = D_t + E[M_{t,t+1}V_{t+1}(\Theta_{t+1})] \tag{16}$$

$$\Longrightarrow 1 = E\left[M_{t,t+1}R^s_{t+1}\right] \tag{17}$$

in which equation (16) is the Bellman equation for the value function, and the Euler equation (17) follows from the standard formula for stock return $R^s_{t+1} = V_{t+1}(\Theta_{t+1})/[V_t(\Theta_t) - D_t]$. Substituting the stochastic discount from equation (14) into equation (17), and some algebra, yields the following equilibrium asset pricing equation:

$$E_t\left[r^e_{t+1}\right] = \lambda_a \times \beta^a + \lambda_s \times \beta^s \tag{18}$$

in which $r^e_{t+1} = R^s_{t+1} - R_f$ 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 $\beta^a = \frac{Cov\left(r^e_{t+1}, \triangle a_{t+1}\right)}{Var(\triangle a_{t+1})}$ and $\beta^s = \frac{Cov\left(r^s_{t+1}, \triangle s_{t+1}\right)}{Var(\triangle s_{t+1})}$ are the sensitivity (betas) of the firm's excess stock returns with respect to the two aggregate shocks in the economy.

According to equation (18), 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 (14). The pre-specified sign of the loadings imply a positive price of risk of both the aggregate productivity shock and the frontier shock. Thus, all else equal, assets with returns that have a high positive covariance with the aggregate productivity shock or the frontier shock are risky and offer high average returns in equilibrium.

4.5 Markups

Following De Loecker, Eeckhout, and Unger (2020), we define the markup as the price-marginal cost ratio. In the model, markup depends on firms' technology adoption decisions. In particular, when firms adoption the frontier technology, i.e., $\phi = 1$, the markup is

$$\mu_1 = \frac{P}{\frac{\partial\left(\frac{f_o(\mathcal{F},\mathcal{T})}{S}K\right)}{\partial Q}} = \frac{P}{\frac{\partial\left(\frac{f_o(\mathcal{F},\mathcal{T})}{S}\frac{Q}{ZX}\right)}{\partial Q}} = \frac{\left(\frac{Q}{B}\right)^{-\frac{1}{\varepsilon}}}{\frac{f_o(\mathcal{F},\mathcal{T})}{S}\frac{1}{ZX}} = \frac{\left(\frac{ZXK}{B}\right)^{-\frac{1}{\varepsilon}}}{\frac{f_o(\mathcal{F},\mathcal{T})}{S}\frac{1}{ZX}} = (ZX)^{1-\frac{1}{\varepsilon}}\left(\frac{K}{B}\right)^{-\frac{1}{\varepsilon}}\frac{S}{f_o\left(\mathcal{F},\mathcal{T}\right)}; \tag{19}$$

when $\phi = 0$, the markup is

$$\mu_2 = \frac{P}{\frac{\partial\left(\frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_N)N}K\right)}{\partial Q}} = \frac{P}{\frac{\partial\left(\frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_N)N}\frac{Q}{ZX}\right)}{\partial Q}} = \frac{\left(\frac{Q}{B}\right)^{-\frac{1}{\varepsilon}}}{\frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta_N)N}\frac{1}{ZX}} = (ZX)^{1-\frac{1}{\varepsilon}}\left(\frac{K}{B}\right)^{-\frac{1}{\varepsilon}}\frac{(1-\delta_N)N}{f_o\left(\mathcal{F},\mathcal{T}\right)}. \tag{20}$$

From the above two equations, we see that 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., $S_t > (1 - \delta_N N_{t-1})$), which leads to a smaller marginal cost of production.

5 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. All of the endogenous variables in the model are functions of the state variables. Because the functional forms are not available analytically, we solve for these functions numerically. Appendix A-2 provides a description of the solution algorithm (value function iteration) and the numerical implementation of the model.

5.1 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. The model is calibrated using parameter values reported in previous studies, whenever possible, or by matching the selected moments in the data reported in Table 6. To evaluate the model fit, the table reports the target moments in both the data and the model. 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 100 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 4.

Firm's technology: general parameters. We set the elasticity of demand curve $\varepsilon = 5$ 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). The capital depreciation rate δ_K is set to be 3% per quarter, as in Bloom (2009). The depreciation of technology capital δ_N is set to 4% consistent with estimated depreciation of intangible capital in Ward (2023).

Firm's technology: adjustment costs and operation costs. We calibrate the capital adjustment cost parameter $c_k = 2.5$ to roughly match the volatility and autocorrelation of the firmlevel investment rates. The model implied volatility and first-order autocorrelation are 0.30 and 0.54, respectively, close to those in the data at 0.18 and 0.54. We calibrate the fixed technology adoption costs $f_a = 2.6$ so that implied adoption frequency is 2 years, close to the low end of estimates reported in Lin, Palazzo and Yang (2021). Given that the technology adoption in the model includes different types of technologies, while Lin, Palazzo and Yang (2021) focus on the new machines and equipment adoption, our adoption frequency captures the more frequent technology adoptions for firms in ICT, information technology, AI, etc.

For parameters with heterogeneity across time and across groups of firms, we calibrate them separately for the pre-2000 and the post-2000 periods. For the mean level of the technology frontier $\bar{s}(\mathcal{T})$, we set it to -0.60 for the pre-2000 economy together with the operating production costs $f_o(\mathcal{F}, \mathcal{T}) = 0.075$ so that the implied markup is 1.60, close to the data. For the post-2000 economy calibration, we calibrate $\bar{s}(\mathcal{T})$ and $f_o(\mathcal{F}, \mathcal{T})$ for low markup group and high markup groups by targeting the aggregate markup and the group-specific markups. This leads to an $\bar{s}(\mathcal{T}) = 0.156$, and $f_o(\mathcal{F}, \mathcal{T}) = 0.26$ and 0.03 for the low and high markups respectively.

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 $\rho_x = 0.913$ and the conditional volatility to be $\sigma_x = 0.080$ to match the volatility of aggregate profits. 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 $\rho_s = 0.941$ and the conditional volatility to be $\sigma_s = 0.122$ to match aggregate stock market volatility as closely as possible, while keeping the investment rate volatilities at reasonable values, given the calibrated adjustment cost parameters.

To calibrate the persistence and conditional volatility of the firm-specific productivity shock, we use $\rho_z = 0.913$ and $\sigma_z = 0.2$. The long-run average level of firm-specific productivity, $\bar{z}$, is a scaling variable. We set $\bar{z} = -1.3$, 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 ($\gamma_x = 0.1$, and the loading of the stochastic discount factor technology frontier shock to be ($\gamma_s = 1$ by matching the average aggregate stock market excess return and hence the aggregate Sharpe ratio in both the data and the model.

5.2 Policy functions

Figure 5 illustrates the technology adoption policies with respect to the technology capital, where we scale the technology capital N_{t-1} by $\max N_{t-1}$ for comparison across different economics. When the current technology capital is small, the adoption benefit is large so that the firms choose to adopt and the technology shock jumps to the technology frontier S_t. While when the current technology capital is large, the firms would not adopt since the adoption benefit is small. The middle panel shows that in the economy after 2000, the low group's adoption region becomes smaller 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 the high group's adoption region becomes larger due to the smaller cost $f_o(\mathcal{F}, \mathcal{T})$.

Figure 6 describes how the scaled technology frontier shock $\frac{S_t}{\max S_t}$ affects markup. When the current technology frontier shock is small, the firms do not adopt and the markup is constant according to equation (20). When the current technology frontier shock is large, the firms choose to adopt and the markup increases in the technology shock from equation (19). Comparing to the economy before 2000, the firms of the low group after 2000 have a smaller markup and less adoption due to the larger cost $f_o(\mathcal{F}, \mathcal{T})$. While the firms of the high group after 2000 have a larger markup and more adoption due to the smaller cost.

The jump of the markups come from the technology adoption. For a given current technology capital, if the firms start to adopt at a higher technology frontier, the difference of $S_t - (1 - \delta_N)N_{t-1}$ 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.

5.3 The evolution of the value premium and markups

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.

5.3.1 Pre-2000 economy

Table 6 reports the model implied moments for the pre-2000 economy. Overall the model fits the data reasonably well; in particular, it generates a large value premium and a low markup. The model implied asset pricing moments, e.g., the market returns, Sharpe ratio and the risk-free rate are 6%, 0.39 and 1.65% in the model, close to the data moments of 6%, 0.39 and 1.5%. The model implied quantity moments, e.g., firmlevel investment rate volatility and autocorrelation are 0.30 and 0.54, close to the data at 0.18 and 0.54, respectively. Furthermore, the model also generates a sizable value premium of 5.4%, close to the data at 5.7%. Lastly the model implies a markup of 1.6, close to the data of 1.66. 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 1.6% 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.

5.3.2 Post-2000 economy

As noted, motivated by Aghion et al. (2022), to capture the difference between the before- and after-2000 economies, we assume there is an increase in the efficiency ($\bar{s}(\mathcal{T})$) of the aggregate technology frontier that would benefit all firms. In addition, to capture the heterogeneity across groups with different markups, we vary the marginal production costs $f_o(\mathcal{F}, \mathcal{T})$ to generate with low and high markups. These increase in the efficiency of the technology frontier leads to a high average markup of 2.37, close to the aggregate markup in the data of 2.13 for the post-2000 economy.

The heterogeneous marginal production costs directly imply different adoption benefits. In particular, lower marginal production costs implies higher technology adoption benefit and hence firms more likely to choose to adopt the frontier technology; moreover they are also the firms with high markups because the marginal operating costs are small. 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 1.2% (somewhat higher than the data of -3%). Furthermore, the same firms that adopt the frontier technology are also the ones with the higher markup at 3.3 (close to the data), which in turn drives the aggregate markup to increase.

In contrast, firms with higher marginal production costs have lower technology adoption benefit, and hence lower probability 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 as a result. Moreover, these firms are also those with lower markups, as the marginal cost of production remains high. This implies that the risk dispersion among the low markup firms remains large because of the strong operating leverage effect. Hence the value premium remains sizable at 4%, although somewhat short of magnitude than the data of 7.4%. Taken together, we show that the increase in the technology frontier efficiency and the heterogeneity in technology adoption benefit 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.

Lastly the model implied aggregate asset pricing moments including market returns and the Sharpe ratio are close to the data as well (8.92% and 0.35 in the model and 8.79% and 0.57 in the data, respectively).

6 Inspecting the mechanism

In this section we perform several analyses to show the economic forces driving the overall fit of the model.

6.1 The role of cross-time heterogeneity of technology efficiency

One of the key heterogeneities of the model is the cross-time increase in the efficiency of the aggregate technology frontier. To understand the effect of this heterogeneity on the changes of the value premium and markups, we decrease the efficiency $\bar{s}\left(\mathcal{T}\right)$ by a half for the post-2000 economy calibration. Table 7 reports the result (the row of Low efficiency increase in frontier). We find that the average markup becomes 2.11, less than the baseline. More important, for the low markup group, the value premium decreases to 2.65%, much smaller than the baseline. In the model, there are two types of operating leverage in the model. The first is the production costs which is inversely related to adoption, and the other is adoption costs is increasing in the adoption fraction. These two operating leverage tradeoff each other. Because the efficiency of the frontier is less than the baseline, the adoption frequency reduces which leads to a low effective realized adoption costs, and hence the value premium drops; while the markup remains close to the baseline as the marginal production cost does not change. Turning to the high markup group, the markup becomes much smaller than the model 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.

6.2 The role of cross-firm heterogeneity of adoption benefit

Another key heterogeneity of the model is the cross-group difference in the technology adoption benefit, which is determined by $f_o(\mathcal{F}, \mathcal{T})$. Intuitively, the lower $f_o(\mathcal{F}, \mathcal{T})$ is, the higher the adoption benefit is given the technology frontier shock. To understand the effect of the cross-group adoption benefit heterogeneity on the differences in the value premium and markups across firms, we set $f_o(\mathcal{F}, \mathcal{T})$ of the high markup group firms as a half of the low markup group, that is $f_o(\mathcal{F}, \mathcal{T}) = 0.26/2 = 0.13$ (the baseline is 0.03). The row of Low heterogeneity in adoption benefit in Table 7 reports the result, where we keep the same $f_o(\mathcal{F}, \mathcal{T})$ in the low markup group. We find that the value premium of the high markup group increases to 4.47%, much higher than the baseline and the data, while the markup decreases to 1.70 much lower compared to the baseline and the data. Both are counterfactual. 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 leverage channel remains quantitatively an important role for the high markup group, leading to a sizable value premium, opposite to the data.

6.3 The role of market power

In the model, firms face a down-ward sloping demand curve where the market power is determined by the demand curve elasticity parameter ξ. In this section, we increase the market power by lowering ξ from 5 in the baseline calibration to 4. The row of High market power in Table 7 reports the result. In the pre-2000 model economy, we see that the market excess returns decrease from 6.3% to 5.5% and the markup increases from 1.6 to 1.73. This is intuitive, as the firms have more market power, the price is higher the marginal cost, hence the operating leverage is decreasing, resulting in a higher markup and a lower market return. In the cross-section, the dispersion in risk also decreases, generating a lower value premium of 4% less than the 5.4% in the baseline and 5.7% in the data. In the post-2000 model economy, we see that the high markup firms' markup becomes even higher than the baseline model and the data due to the price effect, which in turn also causes the value premium to 1.86%, much smaller than the baseline and the data. For the low markup group, the operating leverage effect decreases due to high market power, hence a smaller value premium and a higher markup than the baseline as well.

7 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 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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Appendix: Numerical Algorithm

When we discrete the AR(1) processes x_t and z_t, we use the method described in Rouwenhorst (1995) for a quadrature of the Gaussian shocks. To set the grid of the $n_t = \log(N_t)$, 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 $\pi^S_{j\to j'}$.

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

$$V_t(K_t, N_{t-1}, X_t, S_t, Z_t) = \max_{I_t,\phi_t}\{D_t + E_t[M_{t+1}V_{t+1}(K_{t+1}, N_t, X_{t+1}, S_{t+1}, Z_{t+1})]\}$$

$$s.t.\ D_t = B^{\frac{1}{\varepsilon}}(Z_tX_tK_t)^{1-\frac{1}{\varepsilon}} - I_t - G(I_t, K_t) - H_t - TC_t, \tag{21}$$

$$\text{where } TC_t = \begin{cases} \frac{f_o(\mathcal{F},\mathcal{T})}{S_t}K_t + f_a & \text{if } \phi_t = 1 \\ \frac{f_o(\mathcal{F},\mathcal{T})}{(1-\delta)N_{t-1}}K_t & \text{if } \phi_t = 0 \end{cases}, \tag{22}$$

$$N_t = \begin{cases} S_t, & \text{if } \phi_t = 1 \\ (1-\delta_N)N_{t-1}, & \text{if } \phi_t = 0 \end{cases}, \tag{23}$$

$$H_t = \begin{cases} (S_t - (1-\delta_N)N_{t-1}) \cdot 1_{\{S_t-(1-\delta_N)N_{t-1}>0\}}, & \text{if } \phi_t = 1 \\ 0, & \text{if } \phi_t = 0 \end{cases}. \tag{24}$$

$$K_{t+1} = (1-\delta_K)K_t + I_t$$

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

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

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

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

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

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

$$\tilde{V}_t^1(K_t, N_{t-1}, X_t, S_t, Z_t) = \max_{I_t} \{D_t + E_t[M_{t+1}V_{t+1}(K_{t+1}, N_t, X_{t+1}, S_{t+1}, Z_{t+1})]\}$$

$$s.t.\ D_t = B^{\frac{1}{\varepsilon}}(Z_t X_t K_t)^{1-\frac{1}{\varepsilon}} - I_t - G(I_t, K_t) - TC_t, \tag{25}$$

$$\text{where } TC_t = \frac{f_o(\mathcal{F}, \mathcal{T})}{(1-\delta)N_{t-1}} K_t, \tag{26}$$

$$N_t = (1-\delta_N)N_{t-1}, \tag{27}$$

$$K_{t+1} = (1-\delta_K)K_t + I_t$$

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

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

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

Under the case $\phi_t = 0$, their technology capital depreciates at the rtae 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 (27). Therefore, numerically we solve the Bellman equation through

$$\tilde{V}_t^1(K_i, N_m, X_q, S_j, Z_p) = \max_{I_t} \left\{ D_t + \sum_{q'=1}^{n_x} \sum_{j'=1}^{n_s} \sum_{p'=1}^{n_z} \pi_{q \to q'}^X \pi_{j \to j'}^S \pi_{p \to p'}^Z V_{t+1}(K_{i'}, N_{m-1}, X_{q'}, S_{j'}, Z_{p'}) \right\}$$

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

$$\tilde{V}_t^2 \left(K_t, N_{t-1}, X_t, S_t, Z_t\right) = \max_{I_t} \left\{D_t + E_t \left[M_{t+1} V_{t+1} \left(K_{t+1}, N_t, X_{t+1}, S_{t+1}, Z_{t+1}\right)\right]\right\}$$

$$s.t.\ D_t = B^{\frac{1}{\varepsilon}} \left(Z_t X_t K_t\right)^{1-\frac{1}{\varepsilon}} - I_t - G\left(I_t, K_t\right) - H_t - TC_t, \tag{28}$$

$$\text{where } TC_t = \frac{f_o\left(\mathcal{F}, \mathcal{T}\right)}{S_t} K_t + f_a, \tag{29}$$

$$N_t = S_t, \tag{30}$$

$$H_t = (S_t - (1-\delta_N) N_{t-1}) \cdot 1_{\{S_t - (1-\delta_N) N_{t-1} > 0\}}. \tag{31}$$

$$K_{t+1} = \left(1 - \delta_K\right) K_t + I_t$$

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

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

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

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

$$\tilde{V}_t^2 \left(K_i, N_m, X_q, S_j, Z_p\right) = \max_{I_t} \left\{ D_t + \sum_{q'=1}^{n_x} \sum_{j'=1}^{n_s} \sum_{p'=1}^{n_z} \pi_{q\to q'}^X \pi_{j\to j'}^S \pi_{p\to p'}^Z V_{t+1} \left(K_{i'}, N_{m'(j)}, X_{q'}, S_{j'}, Z_{p'} \right) \right\}$$

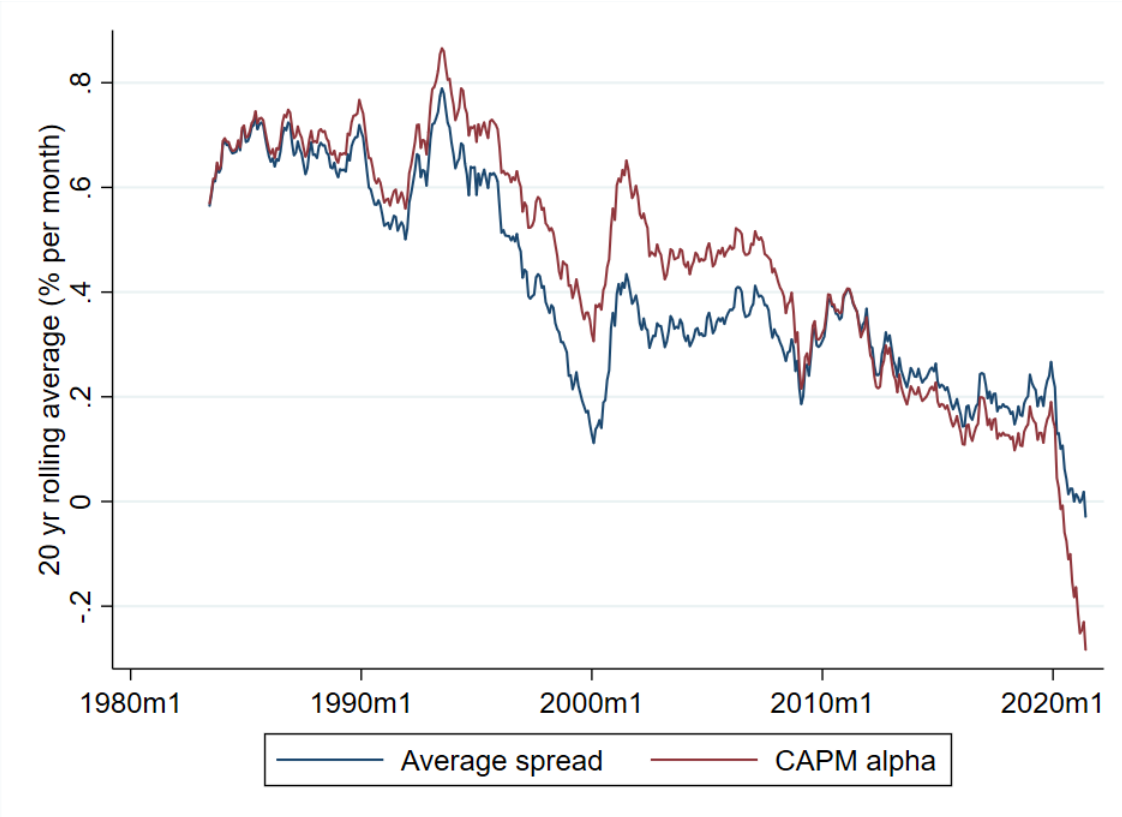
where $N_{m'(j)} = S_j$.

After we solve these two cases, we let

$$V_t \left(K_t, N_{t-1}, X_t, S_t, Z_t\right) = \max \left\{ \tilde{V}_t^1 \left(K_t, N_{t-1}, X_t, S_t, Z_t\right),\ \tilde{V}_t^2 \left(K_t, N_{t-1}, X_t, S_t, Z_t\right) \right\}$$

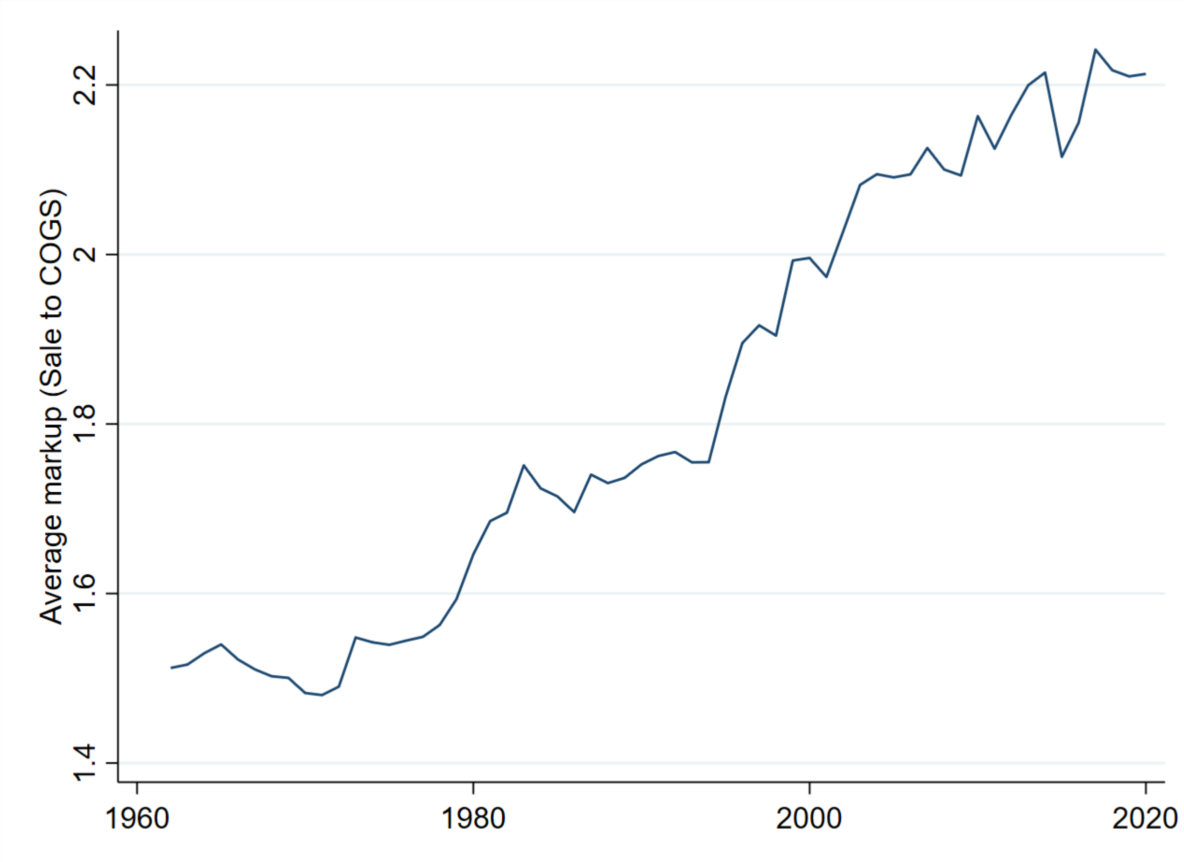
which will tell us whether $\phi_t \left(K_t, N_{t-1}, X_t, S_t, Z_t\right)$ is 0 or 1.

Figure 1: Rolling 20-year average value premium



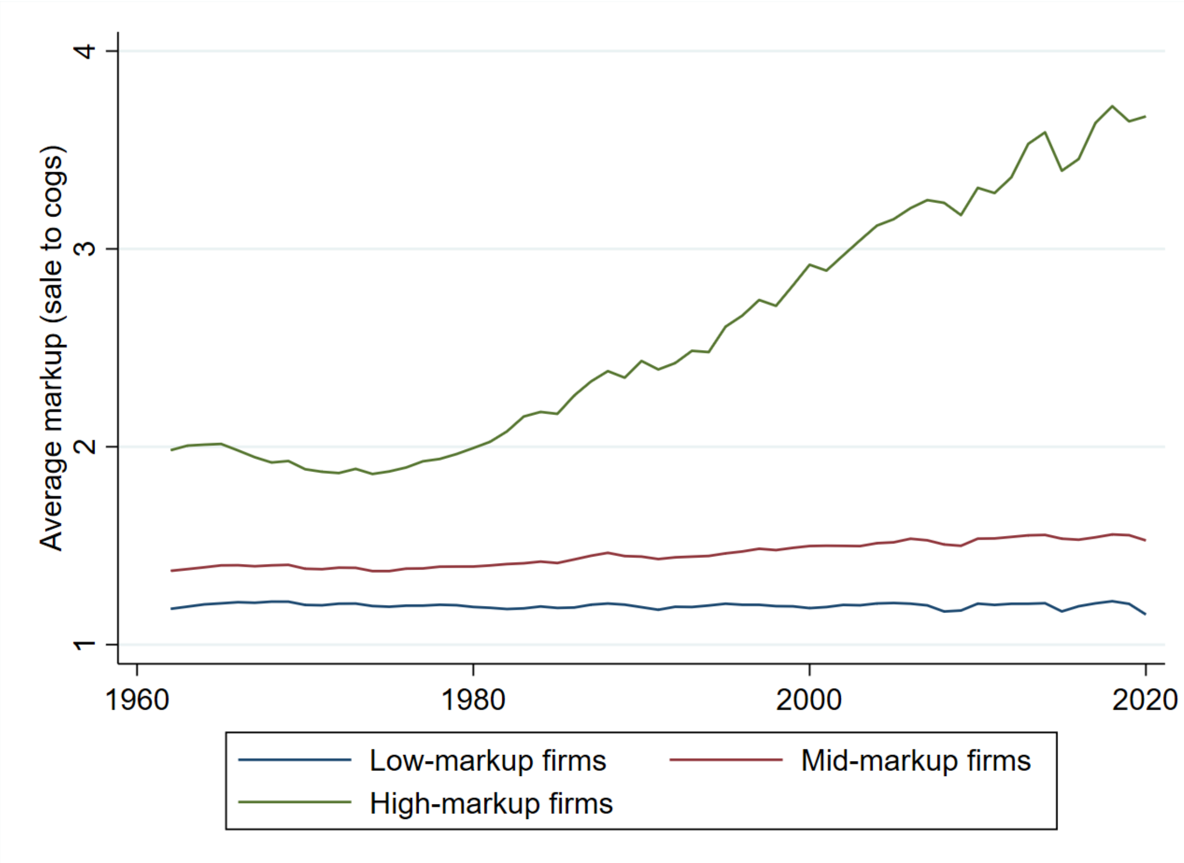
This figure plots 20-year rolling average return and CAPM alpha of top book-to-market quintile (value stocks) minus bottom book-to market-quintile (growth stocks). The sample period is from 1963m7 to 2021m6.

Figure 2: Aggregate markup



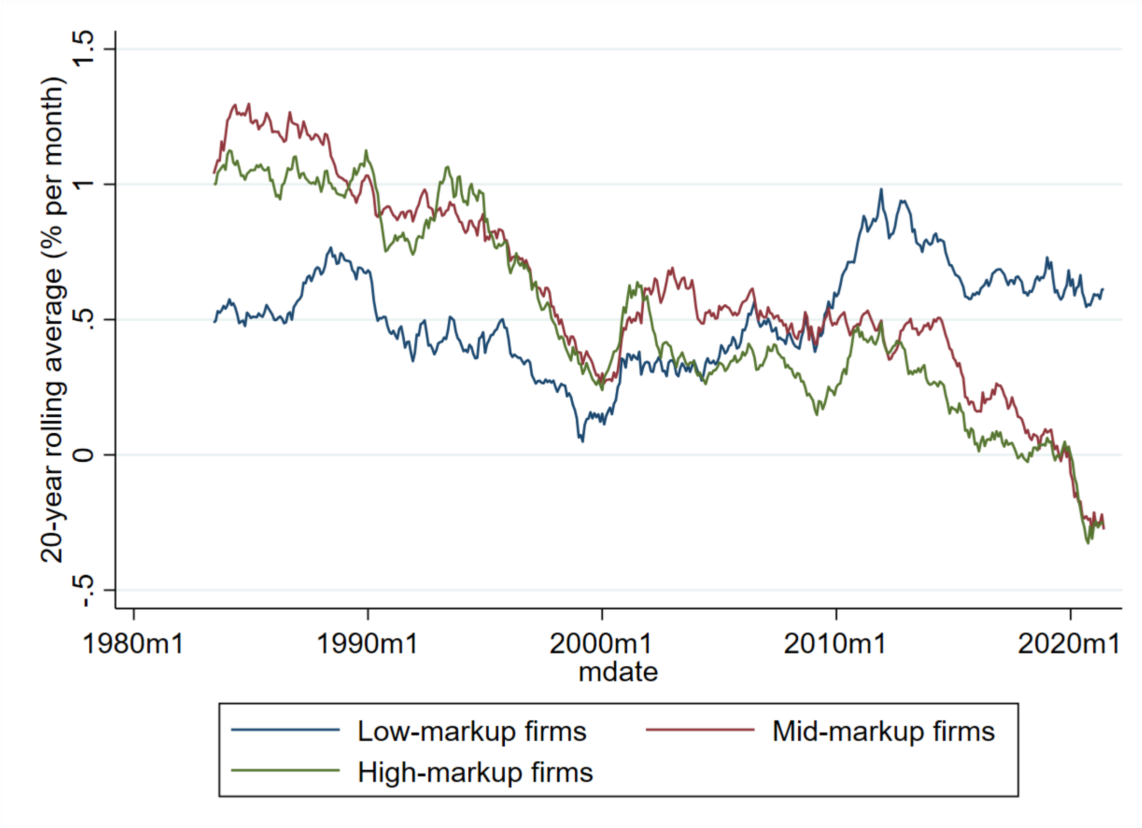
This figure plots the average markup of US public firms (excluding utilities and financials) from 1962 to 2020. We measure markup of a firm as the ratio between its revenue and cost of goods sold.

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



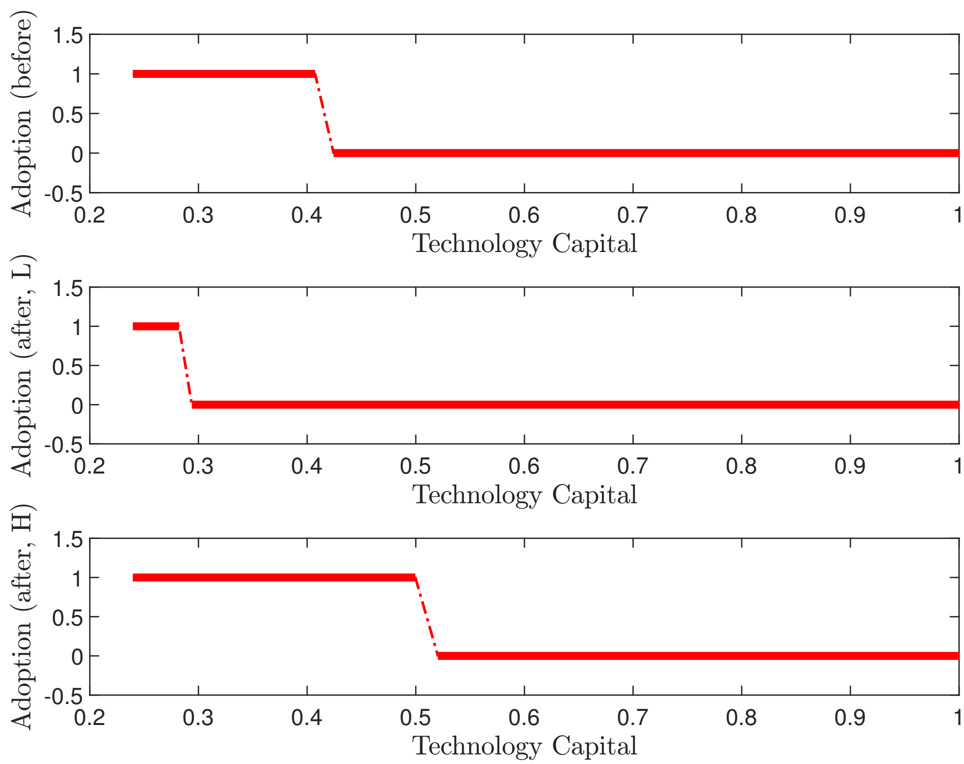
This figure plots the average markup of low, mid and high-markup firms from 1962 to 2020. Low, mid and high-markup firms are defined as firms in the bottom, middle and top NYSE tercile in terms of markup. We measure themarkup of a firm as the ratio between its sales and cost of goods sold.

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



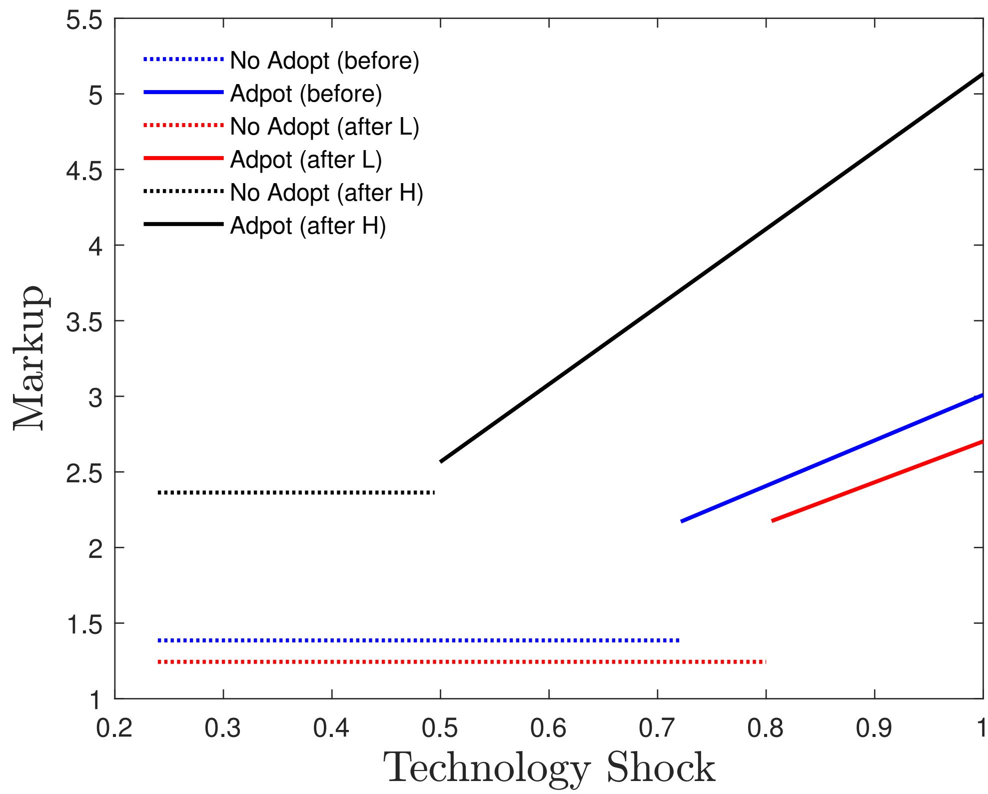
This figure plots the 20-year rolling average value premium among high-, mid-, and low-markup firms. We sort companies into terciles based on their markup and into quintiles based on their book-to-market ratio. We compute value premium in each markup tercile as the value-weighted return of top book-to-market 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: 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 group after 2000, and the high group after 2000 respectively. Other state variables are chosen at the long-run mean of the corresponding economies. All parameters are reported in Table 5.

Figure 6: 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.

Panel A: average excess return from 1963m7 to 2001m6						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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		
The elasticity of demand curve	ε	5
Constant demand shifter	B	1
Rate of depreciation for capital	δ_K	0.03
Rate of depreciation for capital	δ_N	0.04
Technology: adjustment costs		
capital adjustment cost	c_k	2.5
fixed technology adoption cost	f_a	2.6
Stochastic processes		
Persistence coefficient of aggregate productivity	ρ_x	0.913
Conditional volatility of aggregate productivity	σ_x	0.080
Average level of firm-specific productivity	$\bar{z}$	-1.3
Persistence coefficient of firm-specific productivity	ρ_z	0.913
Conditional volatility of firm-specific productivity	σ_z	0.2
Persistence coefficient of operation cost	ρ_s	0.941
Conditional volatility of operation cost	σ_s	0.122
Real risk-free rate	r_f	0.004
Loading of the SDF on aggregate productivity shock	γ_x	0.1
Loading of the SDF on the operation cost	γ_s	1

B: Heterogeneity in parameters				
Parameter	Symbol	Before 2000	After 2000 L	After 2000 H
Long-run mean of technology frontier shock	$\bar{s}\,(\mathcal{T})$	-0.600	0.156	0.156
Operation costs	$f_o\,(\mathcal{F},\mathcal{T})$	0.075	0.26	0.03

Table 6: Selected moments in the data and the Model

This table presents the selected moments implied by the baseline model calibration. 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. Pre-2000 and post-2000 refer to the economy before 2000 and after 2000, respectively. 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.

	Pre-2000		Post-2000	
	Data	Model	Data	Model
Market excess returns	6.05	6.33	8.79	8.92
Sharpe ratio	0.39	0.35	0.57	0.35
Risk free rate	1.47	1.65	-0.87	1.65
Standard deviation of IK	0.18	0.30	0.19	0.33
Auto correlation of IK	0.54	0.54	0.62	0.54
Markup	1.66	1.60	2.13	2.37
Value premium	5.72	5.36	0.09	2.59
CAPM alpha spread of value premium	6.21	2.00	-2.59	-0.22

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; "Low heterogeneity in adoption benefit" is the model specification where the marginal production cost $(f_o(\mathcal{F},\mathcal{T}))$ of the low markup group is set as the half of the high markup group (bigger than the baseline calibration). "High market power" is the model specification where the elasticity of the demand curve ε is set at 4.

Pre-2000					Post-2000								
Agg. Moments					Agg. Moments					Low		High	
Market	SR	Markup	Vol(IK)	ValPrem	Market	SR	Markup	Vol(IK)	ValPrem	Markup	ValPrem	Markup	ValPrem
0. Data													
6.05	0.39	1.66	0.21	5.72	8.79	0.57	2.13	0.20	0.09	1.20	7.37	3.26	-3.05
1. Baseline model													
6.33	0.35	1.60	0.30	5.36	8.92	0.35	2.37	0.33	2.59	1.45	4.00	3.29	1.20
2. Low efficiency increase in frontier													
6.33	0.35	1.60	0.30	5.36	17.07	0.39	2.11	0.48	2.12	1.46	2.65	2.76	1.58
3. Low heterogeneity in adoption benefit													
6.33	0.35	1.60	0.30	5.36	10.64	0.37	1.59	0.38	4.23	1.45	4.00	1.70	4.47
4. High market power													
5.51	0.34	1.73	0.28	4.00	9.19	0.36	2.54	0.30	1.38	1.58	1.86	3.50	0.90

Appendix For Online Publication

We describe additional robustness checks in the data and model.

A 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.

B 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.2 and Table A.3. Table A.2 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.3 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.

C Alternative measures of markup

We use different measures of markup to verify the robustness of our main results. Table A.4 sorts stocks based on their industry-level markup and book-to-market ratio. Panel A of Table A.4 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.4 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.5 calcuates markup based on the measure from De Loecker, Eechhout, and Unger

(2020). The results is similar to Table 3 and Table A.4. In the post-2001 sample period, value premium is much higher among low-markup stocks. Table A.6 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.

D Robustness to excluding micro-cap stocks

We check whether our results are robust to excluding micro-cap stocks. Table A.7 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.8 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.

E Value premium and intangibles

We explore how intangible assets affect value premium. Table A.9 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.10 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 XXX 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.

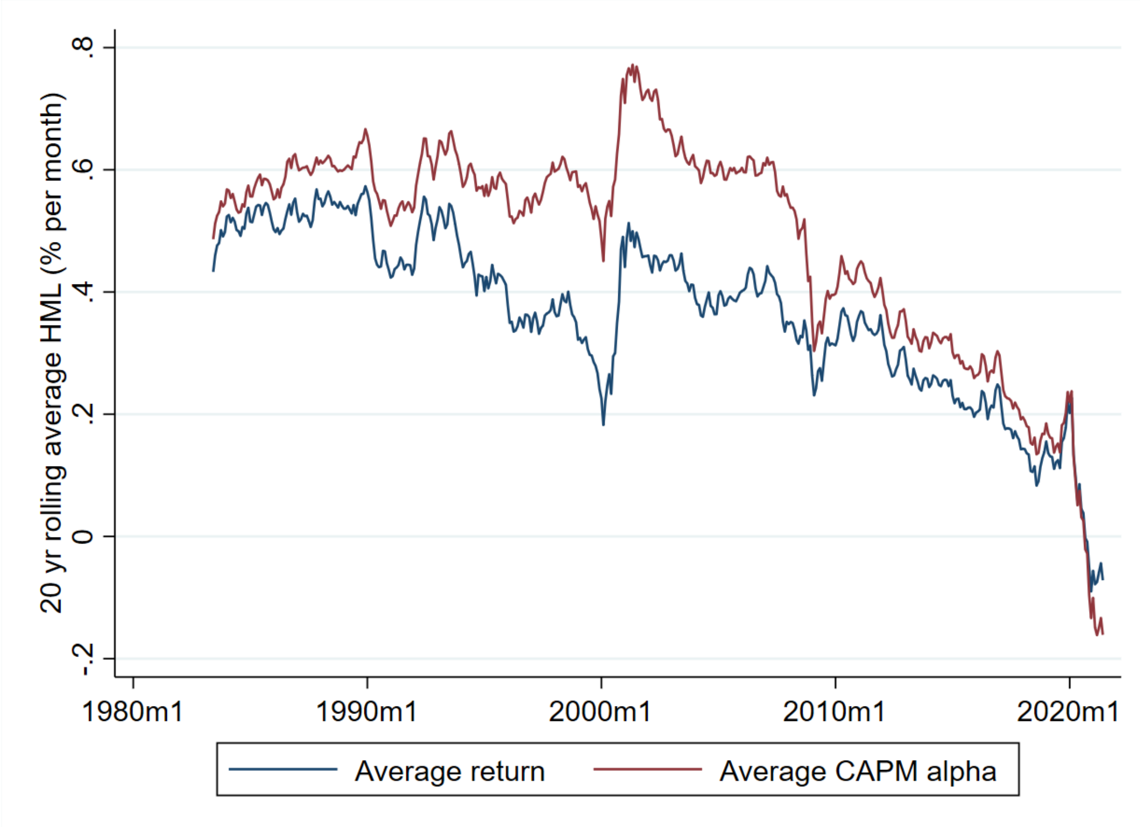
F Asset pricing tests

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.11 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.

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: 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.3: 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.

	(1)	(2)
VARIABLES	change in markup	% 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.4: 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						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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.5: 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.

Panel A: average return 1963m7 to 2001m6						
	Lo BM	2	3	4	Hi BM	Hi-Lo
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 BM	2	3	4	Hi BM	Hi-Lo
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 BM	2	3	4	Hi BM	Hi-Lo
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.6: 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 BM	2	3	4	Hi BM	Hi-Lo
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 BM	2	3	4	Hi BM	Hi-Lo
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 BM	2	3	4	Hi BM	Hi-Lo
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.7: Value premium in low-, mid-, and high-markup firms (exclude 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.8: Value premium in low-, mid-, and high-markup industries (exclude 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.9: value premium and 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.10: intangibles augmented value premium

This table reports the CAPM alpha of stocks sorted by intangible capital augmented book-to-market ratio. We measure intangible capital augmented book-to-market as book equity plus intangible asset and then divided by market cap. Intangible assets are measured as knowledge capital, organizational capital or the sum of knowledge and organizational capital. Knowledge and organizational 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 (knowledge capital + book equity) / market cap						
	Low	2	3	4	High	High - Low
CAPM alpha	0.10	0.11	0.08	-0.17	0.09	-0.01
	(1.08)	(1.47)	(0.76)	(-1.42)	(0.49)	(-0.06)
Panel B: sort by (organizational capital + book equity) / market cap						
	Low	2	3	4	High	High - Low
CAPM alpha	0.12	0.06	-0.03	0.05	-0.06	-0.18
	(1.42)	(0.80)	(-0.29)	(0.34)	(-0.29)	(-0.70)
Panel C: sort by (intangible capital + book equity) / market cap						
	Low	2	3	4	High	High - Low
CAPM alpha	0.14	-0.01	0.05	0.04	-0.06	-0.20
	(1.49)	(-0.19)	(0.49)	(0.36)	(-0.38)	(-0.87)

Table A.11: 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