RISE OF FIRMS WITH NEGATIVE NET EARNINGS

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Abstract

This paper documents the increasing prevalence of public companies with negative net earnings. To begin with, we show that the fraction of firms with negative net incomes has increased sharply from 18% in 1970 to 54% in 2019. Then, we find supporting evidence for both technical change and monetary policy explanations. Lastly, we explore its asset pricing implications and find that longing low net-earnings-to-gross-profitability (or high customer-capital-expenses-to-gross-profitability) firms while shorting the opposite can generate a sizable annualized value-weighted return of 15% (or 24%).

Keywords: profitless firms; customer capital; economies of scale; monetary policy; cross-sectional stock returns

JEL codes: D22; E52; G12; G30; L20; O33

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1 Introduction

Conventional wisdom has it that negative or abnormally low net earnings are bad signals for companies. It indicates that these firms could suffer from at least some cyclical issues or even deeper and long-term problems. However, this argument seems no longer true in the new economy. In the past several decades, we have seen many billion-dollar companies with negative net earnings. We provide some examples in Table 1. Far from being in trouble, these mega-companies are the most popular and highly-owned public companies in the U.S. It seems that they will thrive for years to come.

[Table 1 here]

This paper argues that those mega public companies listed in Table 1 are by no means outliers. As we will see in Section 2, the fraction of profitless firms has increased substantially in the past several decades. Based on the public-firm-level dataset for the U.S. economy, we show that the share of firms with negative *net earnings* has risen from 18.3% in 1970 to 54.4% in 2019. However, most of them are still profitable in terms of *gross income*. When investigating the underlying distributional changes, we find that the mean has considerably shifted to the right over time, which indicates a growing number of mega-firms with huge losses. We also observe a similar upward trend based on the Initial Public Offerings (IPO) dataset. In 1980, only 24% companies were not making money when they went public. However, this number increased to 77% in 2019. Finally, in terms of international evidence, we show that this growing fraction of profitless firms is not unique to the U.S.. Instead, it is a global phenomenon. Additionally, on average, the percentages of firms with negative net earnings are higher in rich countries.

After that, we examine the possible explanations behind this long-run trend. We conjecture that both technological change and the low-interest-rate environment could contribute to the rise of firms with negative net earnings. Then we provide the supporting evidence for both hypotheses. For the technical change story, our main findings are threefold. First, companies, especially these highly profitable ones, have changed their business model substantially in the past several decades. Nowadays, compared to those with low gross profitability, firms with high gross profitability neither invest more in physical capital nor innovate greatly. Instead, they spend considerably more expenses on building up their customer base. Second, firms with higher markups tend to have higher customer capital expenses and lower net earnings. Third, the fraction of firms with negative net earnings is higher in industries with lower marginal production costs. As for the monetary policy hypothesis, we also document three findings. First, falling interest rates increase the relative customer capital expenses of profitless firms compared to profitable ones. In addition, these effects are mainly driven by firms in industries with lower marginal production costs. Second, we do not observe a similar impact of changing interest rates on other corporate expenses such as investment and R&D. Third, our empirical conclusions are robust to the use of high frequency monetary policy shocks as a source of variation in economy-wide interest rates.

Finally, we explore the asset pricing implication of changing corporate behaviors. We document the following four empirical patterns in the data. First, longing low-ratios-of-net-earnings-to-gross-profitability (or high-ratios-of-customer-capital-expenses-to-gross-profitability) firms while shorting the opposite can generate sizable value-weighted returns. The annualized excess return can be as high as 15.32% for net-earnings-sorted portfolios and 23.84% for customer-capital-expenses-sorted ones. Second, the previous cross-sectional return spread cannot be fully explained by the profitability premium (e.g., Novy-Marx, 2013). We show that it is slightly more profitable to long high-profitability-yet-low-net-earnings (or high-customer-capital-expenses) firms and short low-profitability-yet-high-net-earnings (or low-customer-capital-expenses) firms. The annualized excess return can be 15.56% for earnings-profitability-sorted portfolios and 27.00% for customer-capital-profitability-sorted ones. Third, for most cases, the standard asset pricing models such as capital asset pricing model (CAPM), the Fama-French five-factor model (Fama and French, 2015), and the q-factor model (Hou, Xue and Zhang, 2008) are not able to fully capture the net-earnings and customer-capital-expenses return spreads. Finally, to alleviate the concern that some other omitted variables might drive all the previous results, we perform the standard Fama and MacBeth (1973) cross-sectional regressions. We find that even after controlling for other possible return predictors, net income significantly and negatively predicts expected returns for the unprofitable firms. Its economic significance is quite considerable: a one-standard-deviation decrease in the firm's net income is associated with an increase of 0.19% in its monthly expected stock returns.

Related literature Our paper is closely related to four branches of literature. First, our work builds on the literature highlighting the importance of customer capital for industry dynamics.[1] This discussion can date back to the classic *Price & Advertising model* developed by Phelps and Winter (1970), Luptacik (1982), and Feichtinger (1982). After that, many researchers have started to investigate different aggregate implications of customer capital. For example, Rotemberg and Woodford (1992) argue that a dynamic general equilibrium model with oligopolistic competition can generate substantial aggregate demand shocks, which turns out to be important for matching the empirical responses estimated with postwar U.S. data. In addition, Ravn, Schmitt-Grohe and Uribe (2006) investigate how endogenous customer capital choice leads to countercyclical markups. Meanwhile, Dinlersoz and Yorukoglu (2012) show that allowing firms to build up their customer base can substantially shape the equilibrium firm size distribution. In recent years, there has been a growing macro-finance literature on this topic. For instance, Dou and Ji (Forthcoming) use a monopolistic competition with customer capital framework to provide an interesting result

[1] Bagwell (2007) provides an excellent review of the existing literature.

that the optimal markup is pinned down by the trade-off between profiting from current customers and developing potential buyers. Besides, Morlacco and Zeke (2021) investigate the interaction between corporate customer capital expenses and monetary policy. They find that advertisement expenses of large firms are more sensitive to monetary policy shocks than those of small firms. Our contribution is to show that customer capital might be the origin of corporate market power in the new economy, and investigate its corresponding corporate finance and asset pricing implications.

Second, this paper also connects to the changing business dynamism literature. Jones and Philippon (2016) and Gutierrez and Philippon (2017) document this secular stagnation of corporate investment in the U.S.. The major finding in these papers is that from the early 2000s, corporate investment incentives become weaker, despite the increasing profitability and valuation. Specifically, Gutierrez and Philippon (2017) argue that this pattern could come from three different reasons: intangible capital, market concentration, and corporate governance. Some other related studies have documented a similar pattern with data from some European or developing countries (e.g., Lewisi et al., 2014; Bussiere, Ferrara and Milovich, 2015; Kose et al., 2017). Besides, Kilic, Yang and Zhang (2019) discover that the cross-sectional relation between investment and profitability among U.S. public firms has changed from positive to negative in the past several decades. Olmstead-Rumsey (2021) and De Ridder (2019) are the two papers arguing that declining innovation incentives could be the reason behind. Specifically, Olmstead-Rumsey (2021) suggests that the declining innovativeness of market laggards can account for about 40 percent of the rise in market concentration and the 100% productivity slowdown in the past several decades. In contrast, De Ridder (2019) argues that declining marginal costs and rising fixed costs associated with intangible capital contribute to the rise in market concentration. Our contribution is to provide a different explanation for all these trends. We argue that these changes mainly come from companies switching their business model from capital-investment-driven growth to money-burning expansion.

Third, this work contributes to the growing literature on superstar firms. The existing works can be classified into two categories, one focusing on the consequences while the other on the origins of this new superstar economy. For the first category, Autor et al. (2020) and Kehrig and Vincent (2020) argue that the rise of superstar firms is the primary driver of the declining labor share. Similarly, De Loecker, Eeckhout and Unger (2020) claim that the rising markup of large firms could contribute to the declining labor and capital shares and the decrease in labor market dynamism. Besides, Su (2021) investigate how the rise of a risky superstar economy could lead to more internal financing and thus declining capital allocation efficiency. In terms of the second category of the literature, De Loecker, Eeckhout and Mongey (2021) demonstrate that technological innovation and market structure changes contribute to the rise in market power. Compared to the existing literature, this paper focuses on the earnings dynamics in a winner-take-all economy. More importantly, we establish a new fact in addition to the growing literature on changing firms' behaviors. Most of the existing studies are focused on changes in corporate internal financing (e.g., Bates, Kahle and Stulz, 2009), investment (e.g., Gutierrez and Philippon, 2017), or profitability (e.g., Davis, Sollaci and Traina, 2021). In contrast, we investigate the trends in the fraction of firms with negative net earnings.

Finally, our paper is closely related to the growing literature on corporate behavior and asset prices. For instance, Gomes, Kogan and Yogo (2009) document and explain the cross-sectional relationship between product durability and asset prices. Belo, Lin and Bazdresch (2014) study how labor hiring affects cross-sectional stock returns. Bustamante and Donangelo (2017) investigate the two different channels through which product market competition affects expected returns (i.e., operating leverage channel and entry threat channel), and they document an overall negative relationship. Corhay, Kung and Schmid (2020) build a general equilibrium model to jointly investigate how competition and expected returns interact in both the time series and in the cross-section. Finally, Dou, Johnson and Wu (2022) introduce the idea of strategic competition and tacit coordination to explain the close link between fluctuations in discount rates and fluctuations in competition intensity. Our focus is on the cross-sectional return spread in net earnings and customer capital expenses. In addition, our work also complements the existing empirical asset pricing literature such as the profitability premium (e.g., Novy-Marx, 2013).

Layout The rest of the paper is organized as follows. Section 2 provides the empirical evidence on secular trends in the fraction of firms with negative net earnings. In Section 3, we provide several empirical evidence supporting the technical change and monetary policy explanations. Furthermore, Section 4 explores the asset pricing implications. Finally, Section 5 concludes.

2 Long-term Trend

2.1 Data and Variable Construction

Data used for our empirical analysis in this U.S. is mainly obtained from *Compustat*, which contains balance-sheet information for publicly listed U.S. companies. We keep all the entries with a foreign incorporation code of "USA", exclude financial firms (SIC 6000-6999) and regulated utilities (SIC 4900-4999), and drop firms with missing/negative values on assets or sales.[2] For global firms, we obtain the data from *Global Compustat* dataset, and we conduct similar data cleansing processes. Likewise, *Global Compustat* dataset also provides rich firm-level balance-sheet information. It covers publicly traded companies in more than 80 countries, and represents over 90% of the world's market capitalization.

[2] One exception is that we do not exclude financial firms when we explore the industry heterogeneity in these trends.

All variables are constructed by following some recent studies or the standard practice in the empirical corporate finance literature. We obtain a firm's net earnings from *Compustat* data item *NI*. This item reports the income or loss of a certain company after subtracting *all* expenses and losses from all revenues and gains. In contrast, a company's gross profit (*Compustat* data item *GP*) only subtracts cost of goods sold (*Compustat* data item *COGS*) from total revenue (*Compustat* data item *REVT*). Following the work of Morlacco and Zeke (2021) and Peters and Taylor (2017), we measure firms' expenses on customer capital by computing the net selling, general, and administrative expenses (net XSGA), which is the difference between *Compustat* data item *XSGA* and data item *XRD*. We adopt this approach because expenses on salespeople, marketing, and advertising are usually reported directly in the "Selling, General and Administrative Expenses" (*Compustat* data item *XSGA*). However, in *Compustat* dataset, this item also contains R&D expenditures (*Compustat* data item *XRD*). Therefore, following the existing studies, we use the difference between these two as a proxy for customer capital expenses. To measure firm-level markup, we adopt the methodology proposed by De Loecker, Eeckhout and Unger (2020). Generally speaking, a firm's markup is estimated as the product between the elasticity of output concerning variable inputs and the revenue share of each variable input.

In addition, we also include some other firm-level characteristics when conducting our empirical analysis. A firm's output is defined as the net sale or turnover (*Compustat* data item *SALE*) and firm size as the natural logarithm of total assets (*Compustat* data item *AT*). Firm age is computed as the year difference from its first appearance in *Compustat*. The book leverage is computed as the ratio of total debts to the sum of total debts and common equity. We measure a firm's return of asset as income before extraordinary items (*Compustat* data item *IB*) scaled by total assets. Asset tangibility is the fraction of physical assets in total assets. Investment is obtained as the capital expenditures (*Compustat* data item *CAPX*) scaled by total assets. R&D activities are measured as research and development expenses divided by total assets. Dividend payouts of different firms are captured by dividends (*Compustat* data item *DVC*) scaled by total assets. For all nominal variables, we deflate them by using the annual national consumer price index (CPI) obtained from the U.S. Bureau of Labor Statistics (BLS).

Finally, cross-country information on real GDP per capita is obtained from Penn World Table (PWT) and computed as output-side constant-price real GDP divided by total population.

2.2 Evidence from the U.S. Public Firms

2.2.1 Aggregate trends

Figure 1 presents our baseline result on the time series of the fraction of firms with negative net incomes. More specifically, in each year, we count the number of firms with negative net incomes and divide it by the total number of firms. We provide two different indicators: one is weighted by the relative output share of the industry that a firm belongs to, and the other unweighted. As we can see from Figure 1, there is a steady increase in the share of firms with negative earnings for both measures. For the unweighted indicator, only a fraction of 18.3% firms had negative net incomes in 1970. However, this number increased to 54.4% in 2019. As for the weighted indicator, this number has changed from 14.8% in 1970 to 37.4% in 2019. Although there is a significant drop around 2000, this upward trend has picked up in recent years. To sum up, based on this simple exercise, we document a secular upward in the fraction of unprofitable public firms in the U.S.

[Figure 1 here]

Robustness checks We have implemented several different robustness checks. To begin with, we show that this upward trend is not limited to one specific industry. In Figure A1 in the appendix, we plot the share of unprofitable firms for each of the following ten industries: Agriculture, Forestry, & Fishing (SIC 01-09); Mining (SIC 10-14); Construction (SIC 15-17); Manufacturing (SIC 20-39); Transportation & Public Utilities (SIC 40-49); Wholesale Trade (SIC 50-51); Retail Trade (SIC 52-59); Finance, Insurance, & Real Estate (SIC 60-67); Services (SIC 70-89); and Public Administration (SIC 90-99). As we can see from Figure A1, the share of unprofitable firms has been increasing steadily in most of these ten industries. In addition, the most pronounced pattern happens in the manufacturing sector, services sector, and public administration sector. In contrast, this pattern is less apparent in industries like finance and insurance. We argue that this upward trend is important to the whole economy because the manufacturing and services industries are essential in any developed country.[3]

Then we test whether this phenomenon is driven by the increasing fraction of young firms in *Compustat* dataset. Nowadays, we may have substantially more young public firms. In addition, these young firms usually have low net earnings. As a result, the increasing fraction of unprofitable firms could purely come from the age effect. To alleviate such concern, in Figure A2 in the appendix, we provide the time series of two age-related indicators. The first one is average firm age, which is presented as the yellow line in Figure A2. As we can see, the average firm age increases over time, which implies that nowadays, on average, we have more mature public firms. The second proxy is the fraction of young firms. Our definition of young firms is these companies with five years or less. This choice of criterion is *ad hoc*, but our conclusion does not depend on this specific criterion. Based on the green line in Figure A2, we can observe that the fraction of young firms fluctuate around some value over time. There is no clear upward trend associated with this indicator.

[3] We list 2019's top 50 companies with negative net earnings according to their market capitalization in Table A1 in the appendix. As we can see from this list, it covers many different industries such as Agriculture, Manufacturing, Retail Trade, and Services.

Finally, we investigate whether this pattern only shows up in any particular stock exchange. As widely known, different stock exchanges have various listing requirements, especially on the financial criteria. Therefore, in Figure A3 in the appendix, we redo our previous exercise but this time separate companies in different stock exchanges. Specifically, the red line in Figure A3 represents the fraction of firms with negative net earnings in New York Stock Exchange (NYSE), the green line is for companies in National Association of Securities Dealers Automated Quotations (NASDAQ), and the yellow line stands for the rest of stock exchanges in the U.S.. As we can see from Figure A3, there does exist some heterogeneity across different exchanges. For instance, in NYSE, this fraction increased from 10.5% in 1970 to 31.4% in 2019. In contrast, in NASDAQ, this number has changed from 15.5% in 1970 to 63.7% in 2019. However, our previous conclusion on the secular rise of unprofitable firms is not limited to one specific stock exchange.

2.2.2 Gross v.s. Net

More interestingly, this upward trend is not striking when it comes to the share of firms with negative gross profits. As we can see from the two dotted lines in Figure 1, the percentage of firms with negative profits has also increased in the past fifty years. However, the overall importance of those companies to the whole economy is limited. Specifically, with the unweighted measure, the share of firms with negative gross profits has increased from 1.7% in 1970 to 10.2% in 2019. As for the weighted measure, this number changed from 1.3% in 1970 to 3.3% in 2019. Therefore, most public firms are still profitable in terms of gross profits. However, many of these companies may seem in trouble as they report negative or abnormally low earnings.

This difference turns out to be crucial for understanding the underlying mechanism. As explained in the following section, the difference between these two profitability measures mainly comes from the substantial increase in customer capital expenses, especially for the right-tail firms with the highest gross profitability. Intuitively speaking, if a company reports positive gross profits but earnings losses, it indicates that its core business is still profitable. This firm has a negative earning simply because it has spent many resources in expanding the scale of its core business. As discussed later, this behavior is rational as firms can benefit more from increasing operating scale in the new economy. In this perspective, current earnings losses imply that firms are in the middle of building up their future advantages.

In addition, the increasing gap between gross profit and net earnings can also help us reconcile the open debate on measuring firm-level markup in the existing literature. De Loecker, Eeckhout and Unger (2020) document that corporate markup has increased substantially in the past several decades. However, some other studies (e.g., Traina, 2021) provide different conclusions. One of the main reasons they obtain different results is that they use different measures of input costs. Traina (2021) use operating expenses but

De Loecker, Eeckhout and Unger (2020) use costs of goods sold. In practice, operating expenses include marketing and management expenses, in addition to production-related costs. In this paper, we argue that companies use those sales and marketing expenses to build up their customer base today, in order to obtain market power in the future. Following this interpretation, we should not include those expenses when measuring the current markup.

2.2.3 Trends in distribution

Now we investigate the underlying distributional changes in companies with negative earnings. We prepare our empirical results in Figure 2 by using the following steps. To begin with, we select all the firms with negative net earnings each year. Then we plot the size distribution of these unprofitable companies. To show the robustness of our conclusion, we choose three different size-related indicators: market capitalization, total sales, and total assets.

[Figure 2 here]

Specifically, to capture the evolution of the entire distributions, we plot the kernel density of each size-related proxy for all the firms with negative earnings in 1980, 2000, and 2019. Similarly, we choose 2019 instead of 2020 to avoid the possible effects of pandemics. The results are presented in Figure 2. Based on this figure, we can see that the size distribution of unprofitable firms has changed substantially over time. From unreported results on long-term changes in different data moments, we discover a substantial increase in the mean and standard deviation over time but a considerable decrease in skewness and kurtosis. In addition, the changes in distribution are mainly driven by the right shifts in the mean, which indicates the increasing popularity of large firms with negative net earnings. Compared to the 1980s, nowadays, we have substantially more mega-firms with negative net earnings. In other words, the examples provided in Table 1 are by no means some outliers. Instead, compared to forty years ago, there is clearly a growing number of billion-dollar companies with earnings losses in the new economy.

2.2.4 Evidence from Initial Public Offerings

Now we supplement our previous analysis with the IPO dataset provided by Jay Ritter.[4] Figure 3 presents the fraction of companies with negative net earnings when they initially went public in the U.S.. Following the common practice, the information related to corporate earnings is measured at the most recent twelve months before going public. Similarly, we estimate the fraction by calculating the ratio of IPO firms with

[4]We obtain the IPO-related information from Jay Ritter's personal website: https://site.warrington.ufl.edu/ritter/ipo-data/.

earnings losses to the total number of firms going public in that year. The solid blue line in Figure 3 represents the time series plot of this indicator. It clearly shows that the share of IPO firms with negative net earnings has increased steadily in the past several decades. More specifically, in 1980, only 24% of firms did not make money when going public. In contrast, this number rose to 77% in 2019.

[Figure 3 here]

More importantly, this upward trend is not entirely driven by the increasing IPOs for IT firms. The gray dotted line in Figure 3 represents how the fraction of IT-related IPOs changes over time. Before 2000, we can observe that the trends in the share of unprofitable IPOs were likely to be driven by the changes in the relative importance of IT firms. However, after 2000, it is no longer the case. Although the share of IPOs with negative income has increased substantially during this period, the fraction of IT stocks remain relatively stable. One possible explanation is the emergence of non-traditional IT companies with earnings losses, such as Tesla and Peloton. This finding is also consistent with our previous evidence documented in Figure A1 that this secular upward trend shows up in many different industries.

2.3 Global Evidence

It is highly possible that the data on the U.S. publicly-traded firms could suffer from some selection bias. In other words, the facts documented before may simply be some unique phenomena that show up in the U.S. only. In order to alleviate such concern, we repeat our former analysis but this time with a global firm-level dataset. Our main results are provided in panel (A) of Figure 4. Again, we present the time-series plots on the fraction of firms with negative net earnings or with negative gross profits. Similarly, we provide two different time series for each variable: one is weighted by the relative importance of the industry that a firm belongs to and the other unweighted. As we can see from the two solid lines in graph (A), there exists a global rise in the share of firms with negative earnings. This conclusion does not depend on which measure we use. More specifically, for the unweighted measure, 2.7% firms in 1987 had negative net incomes. However, this number increased to 29.6% in 2019. As for the weighted measure, this fraction has changed from 1.1% in 1987 to 26.4% in 2019. Same as before, this upward trend is less pronounced when we focus on the share of firms with negative gross profits. According to the two dashed lines in graph (A), the percentage of firms with negative profits has increased a bit in the past thirty years. Nevertheless, the numbers are relatively small. For the unweighted measure, the share of unprofitable firms has increased from 0.8% in 1987 to 5.5% in 2019. In contrast, for the weighted measure, it has grown from 0.2% in 1987 to 4.3% in 2019. To sum up, from our exercise here with the global firm-level dataset, we show that our previous findings with the U.S. firms are a global phenomenon.

[Figure 4 here]

Another interesting finding here is that cross-sectionally, countries with higher real GDP per capita are associated with a higher fraction of firms with negative net earnings. Panel (b) of Figure 4 presents the binned scatter plot between log real GDP per capita and percentage of unprofitable firms in different countries. The blue dash line represents the fitted linear relationship between these two variables. There exists a positive and significant relationship between them in the data: we are more likely to observe firms with earnings losses in rich countries. This positive cross-country relationship is crucial. It indicates that the rise of unprofitable firms may not come from low institutional quality or poor corporate management. The underlying reason could come from either demand- or supply-side stories. In terms of the supply-side story, there may be more high-tech or e-commerce firms in rich countries. These companies usually employ more intangible capital and deliver some characteristics of increasing returns to scale. However, as we will explain later in the next section, these firms need to spend substantial expenses upfront on building up their user networks. Therefore, they are more likely to report negative net earnings before becoming superstar firms with dominant market shares. In terms of the demand-side story, developing countries tend to have less mature financial markets. In addition, the IPO regulation requirements are more strict and thus require higher listing standards. Therefore, firms with negative net earnings are less likely to get IPO approval in emerging countries. Generally speaking, we argue that both sides could play an essential role in explaining this positive and significant relationship across different countries.

3 Explanation

Now we explain the possible reasons behind this long-run trend. We conjecture that both technological change and the low-interest-rate environment could contribute to the rise of firms with negative net earnings. Then we provide the supporting evidence for both hypotheses.

3.1 Conceptual Framework

3.1.1 Technical change and the value of customer capital

In this part we discuss one possible explanation: technical change. We conjecture that this long-run trend could be closely related to the increasing degree of returns-to-scale in the new economy. Some recent studies have shown that since the 1980s, companies in advanced economies have seen substantial reductions in marginal cost of production and hence a major increase in operating scale (e.g., De Ridder, 2019; Hoberg and Phillips, 2021). Here we argue that the increasing scalability could affect firms' optimal decisions on customer capital and their net earnings dynamics.

The theoretical framework in our mind is mainly based on Gourio and Rudanko (2014): the product market has search frictions and companies need to conduct advertisement or other marketing activities to sell their products to potential buyers. In this way, the total number of sales cannot exceed the minimum of customer base and production capacity. An exogenous increase in returns-to-scale makes customer capital more valuable as firms can be easily constrained by their existing customer base.[5]

Additionally, the increasing scalability generates asymmetric impacts on the customer and physical capital expenditure. The underlying mechanism is that changes in the degree of returns-to-scale broadly impacts the marginal cost of production but not so much on the optimal composition of different productive factors. As a result, the optimal investment-to-capital ratio does not increase in scalability, which generates a declining investment-to-profitability ratio in the new economy. This theoretical prediction is consistent with recent empirical findings that there is a secular stagnation of corporate investment in the U.S., despite the rising profitability and valuation (e.g., Jones and Philippon, 2016; Gutierrez and Philippon, 2017).

3.1.2 Monetary policy and heterogeneous responses

Although exogenous changes in scalability could lead to endogenous transformations in the corporate business model, there can be other potential explanations as well. An important one is monetary policy. Many recent studies have discussed the close relationship between the low interest rate and corporate behaviors. For instance, Morlacco and Zeke (2021) shows that the interest rate environment could affect firms' strategic interactions on advertisement. They empirically show and then theoretically explain that large firms spend disproportionately more on customer capital investment under the low-interest-rate environment. Besides, Liu, Mian and Sufi (2019) argue that falling interest rates lead to more concentrated markets as the existing market leaders will invest more aggressively to reduce the future competition with their competitors. In a following work, Kroen et al. (2021) further confirms this conclusion with high frequency interest rate shocks. They find that falling interest rates could favor market leaders through the financing channel as the decline in financing cost for industry leaders is stronger. As a result, in a low interest rate environment, market leaders are able to borrow more to invest more aggressively. Based on these theories and empirical findings, our goal is to investigate whether changes in monetary policy could lead to heterogeneous

[5] More specifically, with Gourio and Rudanko (2014)'s framework, the benefit of having one additional customer today comes from not only an increase in today's sales revenue but also the expected increase in the continuation value of the firm. The second effect arises due to the customer stickiness assumption: the new customer will purchase products from the firm again in the next period with some positive probability. In contrast, the cost of one additional customer is exactly the marginal production cost. These three components jointly determine the marginal value of an additional customer to firms. With this theoretical framework, we can easily see that the marginal value of an additional customer increases when there is a reduction in the marginal production cost. Meanwhile, companies have stronger incentives to spend many customer capital expenses upfront to build up their customer base due to their continuation value. However, earnings will be relatively low when the existing customer base is still small. The net earnings will eventually turn positive when the firm's customer base has reached a certain level. Before that turning point, these companies continue to report high operating expenses and large losses.

responses between unprofitable and profitable firms.

3.2 Technical Change Story

3.2.1 Fundamental changes in corporate business model

Many existing studies have documented the secular stagnation of corporate investment in the U.S. (e.g., Hall, 2014; Jones and Philippon, 2016; Gutierrez and Philippon, 2017; Alexander and Eberly, 2018). This weak investment incentive is quite puzzling as profitability or valuation has been relatively stable or even increased. In this section, we demonstrate that the declining investment occurs during the same time when firms vastly increase their expenses on customer capital, especially for firms with the highest gross profitability.

Time-series changes We begin with the time-series trends for a representative firm and then turn to cross-sectional differences for firms with different gross profitability. The key message for changes over time is shown in Figure 5. We present the time-series plot of average R&D and customer capital expenses in the top graph. Meanwhile, we plot the time series of average production costs and investment in the bottom chart. All these four indicators are scaled by sales for better comparison. As we can see from Graph (A), the aggregate ratio of customer capital expenses to sales has increased steadily from 5.6% in 1970 to 10.5% in 2019. Simultaneously, the R&D-to-sale ratio has changed from 1.0% to 3.3%. In contrast, Graph (B) shows that the average ratio of production costs to sales has declined from 71.9% in 1970 to 66.0% in 2019. Meanwhile, the investment ratio has decreased from 9.0% to 5.8%. Suppose we simply focus on long-run trends in corporate investment. In that case, the overall business dynamism would appear to decrease as firms nowadays have less incentive to conduct capital investment. However, if we investigate these four trends jointly, one possible explanation for the seemingly declining dynamism could be that companies nowadays have changed their business model from investment-led growth to expenses-driven expansion. Our interpretation here is quite different from the existing literature, which argues that the falling competition mainly contributes to the weak corporate investment (e.g., Jones and Philippon, 2016; Gutierrez and Philippon, 2017).

[Figure 5 here]

In addition, our conclusion here is robust to alternative ways of aggregating firm-level information. In Figure 5, we calculate the aggregate ratios of each indicator. In addition, we do not weigh each firm according to its relative importance in the economy. However, in Figure A4 and A5 in the appendix, we present the results of using median value and weight each firm according to their relative economic importance, respectively. As we can see from these two figures, our main conclusion does not change with these modifications.

Cross-sectional difference More importantly, right-tail firms, i.e., firms with the highest gross profitability, behave considerably different from the rest. Figure 6 presents the same dynamics but for firms with different levels of profitability. More specifically, in each year, we classify firms into five different groups according to their gross profitability. After that, for each group of firms, we compute the average values of investment-to-sale, R&D-to-sale, customer-capital-expense-to-sale, and production-cost-to-sale ratios. In Graph (A) of Figure 6, we show the time series of investment-to-sale ratios for firms at different profitability quintiles. As we can see, before 2000, profitable firms, on average, invest substantially more than other groups of firms. For instance, at the peak year of 1981, the investment-to-sale ratio for the top 20% profitable firms has reached 12.8%. In contrast, the investment-to-sale ratio for the bottom 20% profitable firms in the same year was only 3.6%. However, this pattern has changed considerably in the past decades. In 2019, the investment-to-sale ratio for the top 20% profitable firms was 3.5%, and that for the bottom 20% was 3.0%. The difference becomes quite negligible. This broken-link between investment and profitability is similar to Kilic, Yang and Zhang (2019)'s work, but here we represent their key conclusion in a different format.

[Figure 6 here]

Meanwhile, those highly profitable firms spend vastly on their customer capital. As shown in Graph (B) in Figure 6, there is a significant divergence in customer capital expenses among firms with different gross profitability. Such a gap has been increasing steadily in the past fifty years. More specifically, the average customer-capital-expenditures-to-sale ratios for the top 20% and the bottom 20% profitable firms in the 1970s were 30.3% and 7.9%, respectively. However, in the 2010s, these numbers have changed to 54.4% and 15.1%. In other words, the gap in customer capital expense has risen from 7.2% to 24.1% in the past fifty years. What is surprising is that profitable firms tend not to innovate much more than others. In the bottom left graph in Figure 6, we present the time series of R&D-to-sale ratios for firms at different profitability quintiles. As we can see from this graph, R&D expenses among the least profitable firms have increased substantially in the past fifty years. Meanwhile, the innovation incentive of the rest groups has been stable or increasing modestly.

To sum up, compared to their counterparts fifty years ago, firms in the new economy have changed their business model to a large extent. We find that highly profitable firms do not invest or innovate more than others. Nevertheless, they do spend substantially more on customer capital. These findings suggest that the business dynamism may not have declined, as argued in the existing literature. Instead, the stagnation of corporate investment might come from the fact that companies have changed their focus from physical capital to customer capital. As we will see from the following section, such changes is closely related to the rising corporate market power.

3.2.2 Origins of markup

Here we argue that the origins of corporate markup may come from their customer base. A growing number of studies have documented a substantial increase of average markups in both the U.S. and many other advanced economies (e.g., Nekarda and Ramey, 2013; De Loecker, Eeckhout and Unger, 2020; Eggertsson, Robbins and Wold, 2018; Calligaris, Criscuolo and Marcolin, 2018). These patterns in the data indicate that firms' market power has been steadily increasing in today's economy. Meanwhile, many studies attempt to uncover the origins of corporate markup. For instance, Gutierrez and Philippon (2017) focus on the weak competition story, meanwhile Liu, Mian and Sufi (2019) highlight the role of low interest rates in contributing to the rise of market power. Besides, Crouzet and Eberly (2018) and Bessen (2016) focus on the intangible-capital or IT-capital origin of corporate market power, respectively. Finally, Dopper et al. (2021) propose that changing consumer preference could also lead to rising markups because they find that customers have become less sensitive to price over time.

Our key evidence on the link among customer capital and market power can be best illustrated in Figure 7. Specifically, we compute the firm-level markup and customer capital expenses for all the firms in our sample. Then in each year, we compute the cross-section correlation between these two indicators across different firms. The solid lines are our estimated values, and the shaded areas represent the 95% confidence intervals. The orange line in Figure 7 clearly shows that a firm's markup is positively and significantly correlated with its customer capital expenses. In other words, this positive relationship implies that companies with more customer capital expenses have higher markups on average. More importantly, this cross-sectional correlation has been steadily increasing over time, indicating the increasing importance of the customer base in explaining corporate markup.

[Figure 7 here]

Similarly, we can obtain the time-varying correlation between a firm's markup and its net earnings. The blue line in Figure 7 shows that the cross-sectional correlation between a firm's net income and its markup has changed from positive to negative. This change in the sign of correlation implies that different from our conventional wisdom, nowadays, firms with more negative net earnings are associated with higher market power. In other words, firms with higher markup are still highly profitable in terms of gross profitability. However, as they have stronger incentives to spend substantial resources on customer capital, their net earnings become negative.

Here we want to give a simple model framework to explain why we should expect these relationships in the data. Consider a firm that has a new product to sell. Its innovation cost is a fixed cost of f, and the marginal cost of selling it to an additional customer is c. Therefore, if the total number of buyers is q, then given the product price p, the firm's net income is computed as $\pi = pq - f - cq$. Following the standard literature, a firm's markup is defined as its total profits over total costs, which is by definition $\mu \equiv \frac{pq}{f+cq} = \frac{p}{f/q+c}$. Suppose we live in a new economy with a higher fixed cost f and nearly zero marginal cost c (De Ridder, 2019). Given the market price p, a firm's markup should be positively related to its customer base q, i.e., μ is increasing in q. In other words, if a firm can increase its customer base by spending more on customer capital, its markup will increase even the price remains unchanged. Meanwhile, its net income will decline due to increased customer capital expenses. As a result, we should observe a positive relationship between a firm's customer capital expenses and its markup, but a negative association between its net income and markup in the data.

Generally speaking, we find that firms with higher markups are more likely to be those with higher customer capital expenses and lower net incomes. One caveat for this conclusion is that the correlation between net income and markup might not be negative forever. This negative sign simply implies that, at this point, many companies are still on their way to becoming superstar firms. Once the industrial concentration has reached certain levels, most firms with large customer bases will have started making positive earnings. In that case, this cross-sectional correlation will likely become positive again.

Finally, we implement some reduced-form fixed-effect regressions to show that our previous conclusion is robust to introducing some additional control variables. The regression results for investigating the association between firm-level markup and customer capital expenses are presented in Table 2. The general model specification used in Table 2 can be shown as follows:

$$\text{markup}_{i,t} = \alpha + \beta \times \frac{\text{net XSGA}_{i,t}}{\text{sale}_{i,t}} + \Gamma X_{i,t} + \delta_i + \mu_t + \varepsilon_{it}$$

Throughout this part, i and t refer to firm and year, respectively. The variable markup is the firm's estimated markup, and $\frac{\text{net XSGA}_{i,t}}{\text{SALE}_{i,t}}$ here represents our empirical proxy for firm's customer capital expenses. We are primarily interested in the sign and statistical significance of the estimated coefficient β. In addition, X represents a set of firm-level control variables that could affect companies' customer capital expenses. Following the empirical corporate finance literature, we include the return of assets, tangibility, investment, size, profitability, book leverage, dividend payout, cash-to-asset ratio, and Tobin's q. For most columns, we control both firm- and year-fixed effects to account for the unobserved firm and year characteristics, except for the last two columns. All standard errors are clustered at the firm level (or industry level for the last two columns).

[Table 2 here]

Columns (1) - (9) in Panel A of Table 2 present our baseline results using the fixed-effect regression model, with a slight difference in the choices of control variables in each column. In the last three columns, we include all the firm-level control variables. The difference between the last three columns comes from the choices of fixed effects: In column (10), we control for firm and year fixed effects; In column (11), we include 3-digit SIC industry and year fixed effects; Meanwhile, in the last column, we introduce the industry, year, and industry-year fixed effects. Based on the results shown in Table 2, we can find that in all specifications, the estimated coefficients of the firm's customer capital expenses are positively significant. In addition, for most of them, the estimated coefficient enters with a positive sign at the 1% significance level. It suggests that companies' markups are significantly and positively associated with their customer capital expenditures. In terms of economic significance, our empirical results in Table 2 show that one standard deviation (0.45) increase in customer capital expenditure is associated with a 1.0-2.72 percentage points increase in corporate markup, which is equivalent to an increase by 0.04-0.11 standard deviations. This result implies an economically significant relationship between these two indicators.

3.2.3 Identification with cross-industry heterogeneity

Last but not least, we test whether the fraction of firms is higher in industries with higher returns-to-scale. In order to conduct this empirical investigation, first, we need to obtain measures on the industry-level production function. We follow De Ridder (2019)'s methodology to obtain the estimates on fixed cost $\overline{fc}$ and marginal production cost $\overline{mc}$. More specifically, for each year and each industry at the 3-digit SIC level, we use the following two equations for our estimations:

$$\overline{\mathrm{fc}} = \left(1 - \frac{1}{\mathrm{markup}}\right) \mathrm{SALE} - \mathrm{IB} \tag{1}$$

$$\overline{\mathrm{mc}} = \frac{\mathrm{COGS} - \overline{\mathrm{fc}}}{\mathrm{SALE}} \tag{2}$$

Data source and variable constructions of *SALE*, *IB*, *COGS*, and *markup* are the same as those described in Section 2.1. Consistent with other related studies (e.g., De Ridder, 2019; Hoberg and Phillips, 2021; Su, 2021), we also document a secular increase in fixed production cost $\overline{fc}$ and a substantial reduction in the marginal cost of production $\overline{mc}$. In addition, we obtain the industry-year level estimates on the share of firms with negative net earnings as we did in the previous sections.

Figure 8 presents the binscatter plot between our industry-level measure of marginal cost $\overline{mc}$ and share of firms with negative net earnings. The gray dash line represents the linear-fit regression. This figure clearly shows a negative and significant relationship between these two variables: industries with lower marginal production costs indeed have a higher fraction of firms with negative net earnings. This significant and negative association in the data supports our technical change hypothesis. Companies in industries with relatively low marginal production costs face more economies of scale. As a result, they need to go through a rat race in customer base competition before a small number of them become superstar firms.

[Figure 8 here]

We also report the regression results with different controls and fixed effects in Table 3. Based on this table, we can see that this negative and significant association remains robust across various model specifications. In terms of economic significance, our result shows that one standard deviation (0.15) decrease in marginal cost is associated with a 1.47-8.63 percentage points increase in the share of unprofitable firms. The latter is equivalent to an increase by 0.06-0.38 standard deviations. Our empirical finding implies that the close relationship between marginal product cost and the share of unprofitable firms is also economically significant. In other words, the changing economies of scale arising from new technologies such as digitization also transform the corporate business model and the nature of competition between firms.

[Table 3 here]

3.3 Monetary Policy Story

3.3.1 Initial exploration

Now we turn to analyze whether a low-interest-rate environment also nurtures profitless firms. Table 4 provides an initial assessment by computing the time-series correlation between the fraction of profitless firms and various nominal interest rates. The data on different low-frequency interest rates are obtained from Fed St. Louis and the high-frequency interest rate data is obtained from Nakamura and Steinsson (2018) and Acosta (2022). The correlation is measured at the annual frequency as the quarterly data on net income information is not available in *Compustat*. Following the existing literature, monetary policy shocks are aggregated by summing up all the interest rate surprises within each year.

Our initial exploration in Table 4 shows that monetary policy is closely related to the share of firms with negative net earnings. With various interest rate measures, we can find a negative and significant association. In other words, an low interest rate environment is significantly related with an economy with a higher fraction of profitless firms. For all indicators except for the federal funds rate, the negative correlation is significant at the 5% or 1% confidence level. The economic significance is also quite considerable: the magnitude of such a correlation varies from 0.24 to 0.83. In addition, based on our preliminary analysis here, this association is stronger for long-term interest rates, which is consistent with our expectation as long-term interest rates matter more for companies whose major profits may come later in their life cycle.

[Table 4 here]

3.3.2 Monetary policy and customer capital expenses: firm-level evidence

After the initial exploration, we turn to investigate the underlying mechanism behind this significantly negative association. More specifically, we investigate whether the firm-level response to monetary policy varies with corporate net earnings. Based on the existing literature and our empirical results documented in the previous section, we first investigate the heterogeneous impacts on customer capital expenses and then see whether they are different from other corporate expenses such as investment and R&D.

More specifically, our main model specification for all the firm-level regressions in this section can be shown as follows:

$$\frac{\text{net XGSA}_{i,t}}{\text{sale}_{i,t}} = c + a \times \frac{\text{net XGSA}_{i,t-1}}{\text{sale}_{i,t-1}} + b_1 \times \text{Negative}_{i,t} \times \Delta i_t + b_2 \times \text{Negative}_{i,t} + B \times C_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \tag{3}$$

In the equation above, i and t refer to firm and year, respectively. The variable $\frac{\text{net XGSA}_{i,t}}{\text{sale}_{i,t}}$ here represents our empirical proxy for firm's customer capital expenses. $\text{Negative}_{i,t}$ is the dummy equal to 1 when firm i has a negative net earning in year t. Δi_t represents the nominal interest rate changes during year $t-1$ to t. We are primarily interested in the sign and statistical significance of the estimated coefficient b_1. Similar to the previous section, except for the basic regression, we introduce a set of firm-level control variables C that could affect companies' customer capital expenses. In addition, we control both firm- and year-fixed effects to account for the unobserved firm and year characteristics. All standard errors are clustered at the firm level.

[Table 5 here]

Baseline result Table 5 present our empirical results using various two-way fixed-effect regression models. For the first three columns, we use the federal funds rate as our empirical measure for the nominal interest rate. In the first column, we do not include any control variables. In column (2), we add the lagged term, the negativity dummy, and several other variables that possibly affect corporate customer capital expenses. In column (3), we use the interaction term between negativity dummy and the level of interest rates (i.e., $\text{Negative}_{i,t} \times i_t$) instead of changes in interest rates (i.e., $\text{Negative}_{i,t} \times \Delta i_t$). Based on the results shown in Table 5, we can see that across various model specifications, the estimated coefficients of the interaction term are negatively significant at the 5% confidence level. It suggests that monetary policy does affect companies' customer capital expenditures, and there exists some heterogeneous responses for profitable and profitless firms. With falling interest rates, unprofitable companies invest more aggressively in customer capital, compared to profitable ones. In terms of economic significance, our baseline model specification in column (2) of Table 5 show that one standard deviation decrease in nominal interest rate is associated with a 2.3 percentage points relative increase in customer capital expenses for profitless companies. Our result here complements what have been documented in Morlacco and Zeke (2021), which find that compared to small firms, large firms spend more on customer capital after a decline in the interest rate.

Along the yield curve In order to see the heterogeneous effects of various interest rates along the yield curve, in columns (4)- (7), we redo our regression in column (2) but with nominal rates of different maturities. We present the results of using 3-month T-Bill rate, 6-month T-Bill rate, 1-year T-bond rate, and 10-year T-bond rate in columns (4)-(7), respectively. In addition, the regression results with aggregated high-frequency interest rates are shown in the second last column.[6] As we can see from these columns, our main conclusion still holds with different nominal interest rate proxies: after a decline in the nominal interest rate, unprofitable companies spend more in customer capital expenses, compared to profitable ones. Of course, the precise magnitudes of this impact are slightly different. Based on Table 5, such an effect is stronger for changes in the short-term rates.

Industry effect We also find that such an effect only exists in industries with lower marginal production costs. In columns (8) and (9), we split the whole sample into two subsamples: one contains all firms in industries with relatively high marginal production costs, the other includes those in industries with low marginal production costs. The industry-level measure on marginal production costs is the same as in Section 3.2.3. We choose the median value as the threshold, but our empirical results do not depend on this specific choice of sampling criterion. Based on columns (8) and (9), we find that this heterogeneous response to changes in monetary policy are mainly driven by companies in industries with low marginal production costs. This empirical finding is consistent with our previous technical change story that firms with higher returns-to-scale can benefit more from increasing customer base. As a result, these firms are willing to pay more on customer capital expenses.

Quarerly dataset In all our baseline regressions, both the dataset and the measured relationship is in annual frequency, as the firm-level information on net income is only available annually. In column (11) in Table 5, we redo our exercise here with the quarterly dataset. Still, the negativity dummy is measured at the

[6]We will discuss the local projection results with high-frequency monetary policy data in the next section.

annual level, but all the other variables can be quantified at the quarterly frequency. The results in column (11) show that our previous findings are robust to the change of data frequency.

Investment and R&D What's interesting is that the heterogeneous responses to monetary policy for profitable and profitless firms only exist for customer capital expenses, but not for other corporate expenditures such as capital investment and R&D expenses. In Table A2 in the appendix, we re-run all the regressions in Table 5 but this time with different left-hand-side variables. The regression outcomes for using capital investment and R&D expenses as the dependent variable are presented in the Panel (A) and (B) of Table A2, respectively. As we can see from Table A2, after a decline in nominal interest rate, there is no notable difference between profitable and unprofitable firms in terms of their expenses on physical capital and R&D. The heterogeneous responses to changes in monetary policy are limited to customer capital expenses only.

3.3.3 Identification with high-frequency monetary policy shocks

Although our previous results indicate a close relationship between monetary policy and the rise of profitless firms, it may come purely from correlation instead of causality. To alleviate such concern, we adopt the high-frequency monetary policy framework used in the existing literature (e.g., Cook and Hahn, 1989; Kuttner, 2001; Cochrane and Piazzesi, 2002). In this framework, we construct monetary policy shocks by using unexpected interest rate changes over a 30-minutes window around scheduled Federal Open Market Committee (FOMC) meetings. This high-frequency identification approach alleviates the endogeneity concern of other methods including vector autoregression (VAR) (e.g., Christiano, Eichenbaum and Evans, 1999) and narrative approaches (e.g., Romer and Romer, 2004).

Following the existing literature (e.g., Nakamura and Steinsson, 2018), monetary policy shocks are aggregated to the quarterly frequency by summing up all the interest rate surprises within each quarter. In addition, the dynamics of differential responses across firms is estimated using local projections regressions (e.g., Jorda, 2005). More specifically, we adopt the following model specification:

$$\Delta^k \frac{\text{net XGSA}_{i,t}}{\text{Sale}_{i,t}} = \beta_k \times \text{Negative}_{i,t} \times \Delta i_t + \alpha_k \times \mathit{Industry}_i \times \Delta i_t + \gamma_k \times \text{Negative}_{i,t} + \zeta_k \times \text{X}_{i,t} + \varepsilon_{i,t,k} \quad (4)$$

In the model specification above, Δ^k represents the k-period difference between $t+k$ and t for the dependent variable. Industry denotes the 3-digit industry dummy and X is a vector of fixed effects such as firm-by-quarter and industry-by-time fixed effects. Standard errors are clustered by firm and quarter. One caveat is that although other variables are measured at the quarterly level, the negativity dummy is still measured at the annual frequency.

[Figure 9 here]

The estimated β_ks are plotted in Figure 9. The coefficient in this figure can be interpreted as the difference in the relative ratio of customer capital expenditures to total sales between a representative profitless firm and a representative profitable firm after a 100 basis point contractionary monetary policy shock. As we can see from Figure 9, the estimated impacts are negatively significant, which implies that after an increase (decrease) in the interest rate, firms with negative net earnings reduce (increase) customer capital expenditures more than firms with positive net earnings. In addition, such an effect still exists until six quarters after the unexpected monetary policy shock. More importantly, the estimated impacts are also economically considerable. In response to a 100 basis point increase (decrease), unprofitable firms at their peaks reduce (increase) the share of customer capital expenditure in total sales by 7.5 percentage points more than profitable companies.

In this perspective, Figure 9 shows that our main conclusion still holds with this high-frequency monetary policy identification strategy. Following an exogenous and unexpected reduction in interest rates, unprofitable firms increase their spending on customer capital significantly more than profitable firms. In the online appendix, we redo the empirical exercise in Figure 9 but for other corporate expenditures. Same as before, we do not find similar patterns for corporate capital investment (Figure A6) and R&D (Figure A7).

4 Asset Pricing Implication

This section explores the asset pricing implication of the rising profitless firms. We document the following four empirical patterns in the data. First, longing low-net-earnings (or high-customer-capital-expenses) firms while shorting high-net-earnings (or low-customer-capital-expenses) firms can generate sizable value-weighted returns. Second, the previous cross-sectional return spread cannot be fully explained by the profitability premium. Third, for most cases, the standard asset pricing models are not able to fully rationalize the net-earnings and the customer-capital-expenses return spreads. Finally, our Fama-MacBeth regression results show that both net income and customer capital expenses have some predictability power on future stock returns.

4.1 Sorting and Cross-Sectional Returns

In this section, we use the portfolio approach to study the empirical links between net earnings/customer capital expenses and cross-sectional stock returns. We obtain the monthly stock returns information from the Center for Research in Security Prices (CRSP), and all balance sheet data from the CRSP/Compustat Merged Annual Industrial Files. The sample period is from July 1970 to June 2019. We follow the standard data requirements in the existing empirical asset pricing literature: we only select firms with common shares and those traded on the NYSE, American Stock Exchange (AMEX), and NASDAQ. We require that firms have a December fiscal year end so that the accounting information can be aligned across different datasets (Cohen, Gompers and Vuolteenaho, 2002). Finally, we exclude financial firms (SIC 4900-4999) and regulated firms (SIC 6000-6999) in our sample.

4.1.1 Univariate sorting

We start with the standard single sorting approach. We construct five portfolios sorted on the relative ratios of a firm's net earning or customer capital expense to its gross profit. Then we report the portfolio's post-formation average stock returns in the next year. More specifically, our construction steps are as follows. At the end of June of year t, we sort all the common stocks into five portfolios based on its characteristic at the end of year $t-1$ (in our case, the ratios of net earnings or customer capital expense to gross profitability). Once the portfolios are formed, we calculate their returns from July of year t to June of year $t+1$. Portfolios are rebalanced at the end of June for all the following years in our sample.

[Table 6 here]

The first row of Panel (A) and (C) in Table 6 reports the average raw excess stock returns of the five net-earnings-sorted portfolios, as well as the high-minus-low (HML) or low-minus-high (LMH) return spreads and their corresponding t-statistics. Following the existing literature, all the t-statistics are adjusted for heteroscedasticity and autocorrelation in error terms by the Newey-West method with two lags. Panel (A) shows the results of value-weighted returns while (C) lists those of equal-weighted ones. For value-weighted returns, we find that the firm's net-earnings-to-profitability ratio does predict stock returns. Firms with currently low net earnings earn subsequently higher returns on average than firms with currently high net earnings. More importantly, this return spread is also economically large and statistically significant. The average annualized value-weighted return spread (LMH) is 15.32%, and it is significant at the 1% confidence level with a t-statistics of 5.35. However, we do not find any strong evidence for equal-weighted returns. The empirical result in panel (C) shows that the average equal-weighted return spread (LMH) is only 3.03% per annum. More importantly, this value is only marginally significant: the t-statistics is only 1.79. From the fact that the net-earnings return spread is larger in value-weighted returns than in equal-weighted returns, we can infer that this pattern is particularly strong among large firms. Despite that, to alleviate the concern that returns are dominated by some very small firms, we follow the standard practice in this branch of literature and recalculate the cross-sectional stock returns for a subsample excluding micro cap stocks. Consistent with the existing literature, micro cap firms are defined as firms with a market capitalization lower than the bottom 20th percentile of all firms traded on NYSE. The corresponding subsample results for value-weighted and equal-weighted returns are presented in Panel (E) and (G), respectively. These results show that our previous conclusion still holds with this subsample analysis, but the precise magnitudes are slightly different. Now the average value-weighted return spread (LMH) for net-earnings-sorted portfolios becomes 10.98% per annum with a t-statistics of 4.59. Meanwhile, the average annualized equal-weighted return spread becomes 1.46% and it is still insignificantly different from zero.

Then we test whether a firm's customer capital expense also predicts its future stock returns. In panel (B) and (D) in Table 6, we report the corresponding results for portfolios sorted on the ratios of customer capital expenditures to gross profitability. Similarly, for value-weighted returns, firms' customer capital expenses also predict future stock returns. Panel (B) shows that on average, firms with currently high customer capital expenditures earn subsequently higher returns than those with low expenses. As a matter of fact, the return spread here is even larger than that of net-earnings-sorted portfolios. The average annualized value-weighted return spread (HML) for portfolios sorted on customer capital expenses is 23.84%, and this value is more than 6.3 standard errors from zero. Again, we do not find any interesting patterns for equal-weighted returns. Our result in panel (D) shows that the average equal-weighted return spread (HML) is only 2.28% per annum, and it is not significantly different from zero: its t-statistics is only 1.06. As for the subsample excluding micro cap stocks, our conclusions are roughly the same. The average value-weighted return spread (HML) is 16.35% per annum with a t-statics of 5.32. In contrast, for the equal-weighted returns, the spread is only -0.31% and insignificant from zero.

4.1.2 Double sorting

In order to show that our previous results are not mainly driven by the profitability premium (e.g., Novy-Marx, 2013), we extend our previous analysis by investigating the joint link between net earnings/customer capital expenses, gross profitability, and future stock returns in double-sorted portfolios. Based on our empirical finding in Section 4.1.1, for the following exercises, we only focus on value-weighted returns instead of equal-weighted returns.

We form 25 portfolios two-way-sorted on net earnings/customer capital expenses and gross profitability. Our construction steps are explained as follows. At the end of June of year t, we first sort all common stocks into five portfolios based on the firm's relative ratio of gross profitability to total asset. Then, for firms in each of these five profitability portfolios, we further classify them into five portfolios based on the firm's the relative ratio of net earnings or customer capital expenses to gross profitability. Following the existing literature, this sequential sorting guarantees a balanced number of firms in each portfolio. Same as before, all firm-level characteristic information is collected at the end of year $t-1$. Once the portfolios are formed, we calculate their monthly returns from July of year t to June of the next year. We repeat this process at the end of June for each of the following years in our sample.

[Table 7 here]

The Panel (A) in Part I of Table 7 shows that the two-way sorting procedure generates a reasonable spread in average value-weighted excess returns across both the net earnings (rows) and the gross profitability (columns) dimensions. Within the gross-profitability bins (i.e., within each column), firms with low net earnings outperform those with high net earnings. The magnitude is also quite considerable. The average net-earnings return spread across all the gross profitability bins is 17.6% per annum, with a range from 8.20% to 28.09%.

Within the net-earning bins (i.e., within each row), for low net-earnings groups, firms with high gross profitability earn higher returns than those with low profitability. However, the sign is completely reverse for high net-earning bins. Based on these empirical patterns, we can conclude that net earnings at least contains some information about future stock returns that is not absorbed in gross profitability. Meanwhile, longing high-gross-profitability-yet-low-net-earnings firms and shorting the opposite can generate an annual excess return of 15.56%. This magnitude is economically large, and it is significant at the 1% confidence level with a t-statistics of 4.26.

In addition, panel (E) in Part II of Table 7 reports the two-way sorting value-weighted returns for customer capital expenses and gross profitability. The empirical pattern is quite similar. Within the gross profitability bins (i.e., within each column), firms with high customer capital expenses earn higher returns than firms with low expenses by a value between 19.28% to 27.02% per annum. The average annualized net earnings return spread across all columns is 23.4%, which is also economically considerable. However, within the customer-capital-expenses bins (i.e., within each row), except for one case, we do not observe any substantial difference between firms with high gross profitability and those with low profitability. In this way, we can see that customer capital expenses also help predict future stock returns. In addition, we find that longing firms with high-gross-profitability-and-high-customer-capital-expenditures firms and shorting the opposite generate an annual excess return of 27.00%. This spread is also significant at the 1% confidence level with a t-statistics of 6.33.

Not surprisingly, our previous findings can be extended to a subsample excluding micro cap stocks. Panel (I) in Part III and panel (M) in Part IV report the corresponding double-sorted returns for our subsample analysis. Generally speaking, the empirical patterns are pretty similar but the magnitudes now are slightly smaller for the earnings-profitability-sorted portfolios. After excluding the micro cap stocks, longing high-gross-profitability-yet-low-net-earnings firms and shorting the opposite can generate an annual excess return of 8.92%. Meanwhile, longing firms with high gross profitability and customer capital expenditures and shorting those with low gross profitability and customer capital expenditures make an annual excess return of 27.27%. Both of them are significant at the 1% confidence level. Again, after introducing the information of net earnings or customer capital expenses, firms with high gross profitability do not always earn higher returns than those with low profitability. One caveat is that this finding only exists for value-weighted returns. In the unreported equal-weighted returns analysis, for most cases, we are still able to observe the gross profitability premium documented in Novy-Marx (2013), as there is no strong cross-section spread in net-earnings- or customer-capital-expenditures-sorted portfolios.

4.2 Asset Pricing Test

In this section, we investigate the extent to which the variation in the average returns of our double sorting portfolios can be explained by their different exposures to standard risk factors, as captured by the CAPM, the Fama and French (2015) five-factor model, and the Hou, Xue and Zhang (2008) q-factor model. The idea is that if one asset pricing model can capture the cross-sectional variation in stock returns, then the intercept from factor model regressions should not be statistically different from zero.

More specifically, to test the explanatory power of CAPM, we run monthly time-series regressions of the excess returns of each portfolio on a constant (α^{CAPM}) and the excess returns of the market portfolio (MARKET). Following Fama and French (2008), the excess return on the market is measured as the "value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11", and the one-month Treasury bill rate is obtained from Ibbotson Associates. As for the Fama-French 5 factor model, in addition to a constant (α^{FF5}) and the MARKET factor, we include four extra independent factors: SMB (Small Minus Big), defined as "the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios", HML (High Minus Low), defined as "the average return on the two value portfolios minus the average return on the two growth portfolios", RMW (Robust Minus Weak), defined as "the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios", and CMA (Conservative Minus Aggressive), defined as "the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios". Finally, for the Hou-Xue-Zhang q-factor model, in addition to a constant (α^{HXZ}), the MARKET and SMB factors, we also include investment factor IA, defined as "the difference between the simple average of the returns on the six low investment-to-asset portfolios and the simple average of the returns on the six high investment-to-asset portfolios", return on equity factor ROE, defined as "the difference between the simple average of the returns on the six high return-on-equity portfolios and the simple average of the returns on the six low return-on-equity portfolios", and the expected growth factor EG, defined as "the difference between the simple average of the returns on the two portfolios with high expected one-year-ahead investment-to-assets changes and the simple average of the returns on the two portfolios with low expected changes". The intercepts from all these regressions (i.e., α^{CAPM}, α^{FF5}, and α^{HXZ}) are simply the pricing errors or abnormal returns.

The last three rows in each panel of Table 6 report the abnormal returns of our one-sorted portfolios based on firms' characteristics such as net earnings or customer capital expenses. Our main conclusions from this exercise are threefold. First, all the three standard asset pricing models fail to fully explain the cross-sectional return spreads in net earnings. For each panel, compared to the raw excess return spreads, the pricing errors are only slightly lower. More importantly, all of them remain significantly different from zero. For instance, α^{FF5} in the third row of panel (A) indicates that the net-earnings return spread unexplained by the Fama and French (2015) five-factor model is 13.55% per annum, and this number is significantly different from zero with a t-statistics of 12.07. Second, we observe a similar result for portfolios sorted on customer capital expenses. Compared to the raw excess return spread (23.84%), the three asset pricing models can only explain a small fraction. In addition, the unexplained component remains significantly different from zero. Third, our previous conclusions do not depend on whether we look at the full sample or the subsample excluding micro cap stocks. The results in panels (E) and (F) are similar to those in panels (A) and (B), albeit the magnitudes are slightly smaller.

Finally, the last three panels in each part of Table 7 report the pricing errors for our previous double-sorting portfolios. Our main conclusions are fourfold. First, the CAPM does poorly in explaining the cross-sectional returns of all double-sorted portfolios. The pricing errors are only slightly different from the raw excess returns, and all of them remain significantly different from zero. Second, except for the low gross-profitability bin, both the Fama-French five-factor model and Hou-Xue-Zhang q-factor model cannot fully explain the return spread within each column. For instance, for the highest gross-profitability bin, firms with relatively low net earnings still earn more returns than those with high net earnings. The annualized return spread unexplained by the Fama and French (2015) five factor model is 18.49%, and it is significantly different from zero with a t-statistics of 7.61. It implies that our constructed portfolios indeed contain some cross-sectional variations that are not captured by the standard asset pricing models. Third, for most cases, both the five-factor model and the q-factor model are able to explain why it is profitable to long high-gross-profitability-yet-low-net-earnings firms and short the opposite. However, they cannot be used to explain why longing firms with high-gross-profitability-and-high-customer-capital-expenditures firms and shorting the opposite is a profitable investment strategy. Fourth, again, all the previous conclusions do not depend on whether we look at the full sample or the subsample excluding micro cap stocks.

4.3 Fama-MacBeth Regression

The portfolio approach used in the previous sections is convenient, but the return spread in net earnings and customer capital expenses could possibly be driven by other forces not included in our one-sorting or double-sorting analysis. In addition, it is practically impossible to sort on three or more dimensions. As a result, we perform the standard Fama and MacBeth (1973) cross-sectional regressions, to alleviate the concern that some other omitted variables might drive all the results documented in our previous exercises.

More specifically, we run the standard Fama-MacBeth regressions with the following model specification:

$$R_{i,t+1} = \alpha_0 + \beta_1 NI_{i,t} + \beta_2 netXGSA_{i,t} + \Gamma X_{i,t} + \varepsilon_{i,t+1} \tag{5}$$

Throughout this section, i and t refers to stock and month, respectively. In the equation above, R is raw returns in percentage, NI denotes the net income or loss measured in million US dollars, and $netXGSA$ represents the total customer capital expenses also measured in million US dollars. X is a set of control variables including book-to-market ratio, size, and momentum. The first two control variables are measured the same way described in Section 2.1. The momentum variable is calculated the average stock return between the past 1 month and 12 month. Same as before, all the t-statistics are adjusted by Newey-West method with 2 lags.

[Table 8 here]

Our main regression outcomes are presented in Table 8 and our main conclusions are threefold. First, a firm's net income does predict future stock returns, but the sign of predictability is different between profitless and profitable firms. Column (1) reports the result for our full-sample regression. The estimated coefficient β_1 is positive and significant at the 1% confidence level. It implies that firms with currently higher net earnings earn more returns next period, which seems to be inconsistent with our previous findings. However, this result comes from the fact that the sign of predictability depends on whether firms make positive earnings or not. In columns (2) and (3), we redo our Fama-MacBeth regressions, but for two subsamples: one contains all the firms with negative net earnings, the other includes the rest companies. As we can see from the estimated results in these two columns, the sign of predictability is completely different. For the group of firms with negative net earnings, past net income losses negatively forecast future stock returns. More importantly, the magnitude is considerable in economic terms even after controlling for other possible return predictors in the existing literature. For unprofitable firms, a one-standard-deviation decrease in the firm's net income is associated with an increase of 0.13% in firm's monthly expected stock returns. Meanwhile, for profitable firms, the same decline in the firm's net income is only associated with a decrease of 0.015% in firm's monthly expected stock returns.

Second, customer capital expenses always positively predict future expected returns, and the predictability power is stronger for profitless firms. Columns (4)-(6) present the Fama-MacBeth regression results for customer capital expenses with the full sample, the unprofitable-firm subsample, and the profitable-firm subsample, respectively. As we can see from these columns, the estimated coefficients β_2 are all positive and significant at the 5% confidence level. It implies that firms with currently more customer capital expenditures earn higher expected returns in the future. This finding is consistent with what we have seen in the previous sections. However, the magnitudes are not economically significant, after controlling for other possible return predictors. Column (5) shows that a one-standard-deviation decrease in the firm's customer capital expenses is associated with an increase of 0.017% in firm's monthly expected stock returns. This number is even smaller for the profitable-firm subsample and the full sample.

Third, the return predictability of customer capital expenses can be absorbed by net incomes when introducing both of them into the regressions. In columns (7)-(9), we introduce both customer capital expenses and net income into our regressions, and find that the predicting power of customer capital expenses becomes weaker or even insignificant when it coexists with the firm's net earnings information. In contrast, net income variable becomes more economically important in the subsample of profitless firms. Column (8) shows that a one standard deviation decrease in the firm's net income now is associated with an increase of 0.19% in firm's monthly expected stock returns.

5 Conclusion

We document the prevalence of public companies with negative net earnings since the 1970s. We find that the fraction of listed firms with negative net income has increased sharply from 18% in 1970 to 54% in 2019. After that, we examine the possible explanation behind this long-run trend. We hypothesize that both technical change and monetary policy could contribute to the rise of firms with negative net earnings. We provide several sets of empirical evidence to support both hypotheses. Finally, we explore the asset pricing implication of changing corporate business model, and we find that longing low-net-earnings (or high-customer-capital-expenses) firms while shorting high-net-earnings (or low-customer-capital-expenses) firms can generate sizable value-weighted returns.

One caveat is that our main conclusion – the increasing fraction of firms with negative earnings – cannot be generalized to the entire economy with both public and private firms. Based on the unreported exercise, we conducted a similar empirical investigation using the *Orbis* dataset. As widely known, *Orbis* dataset mainly consists of private companies. However, we do not find any apparent trends when investigating the share of firms with negative net earnings in the whole economy. We leave explaining the underlying reason behind this divergence between private and public firms for future research.

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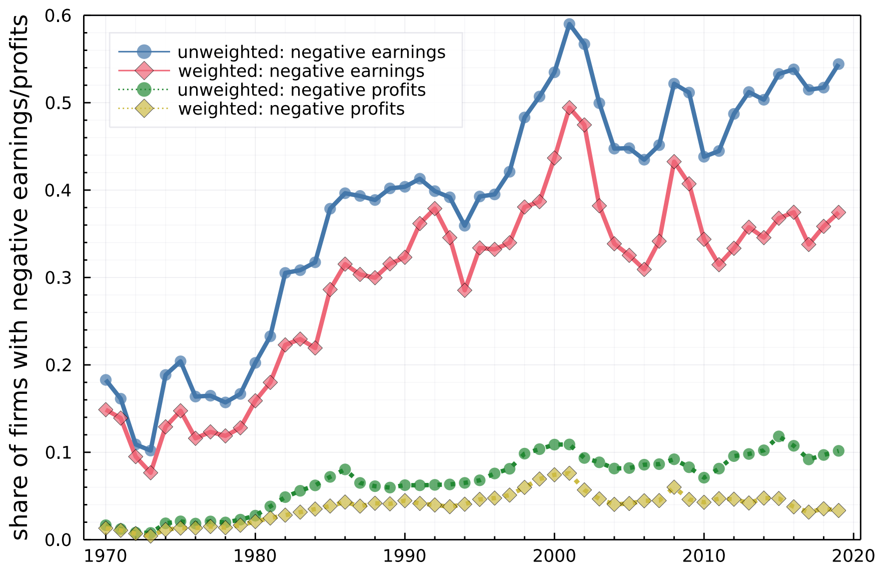
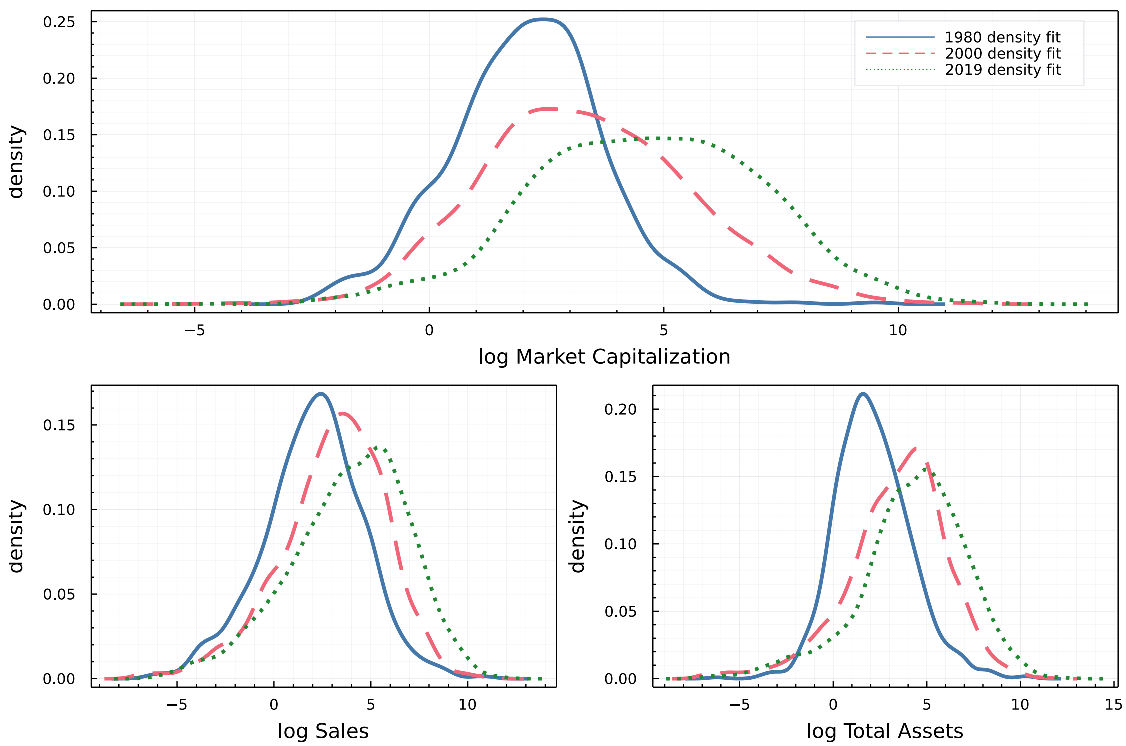
Figures

Figure 1: The Rise of Firms with Negative Net Earnings



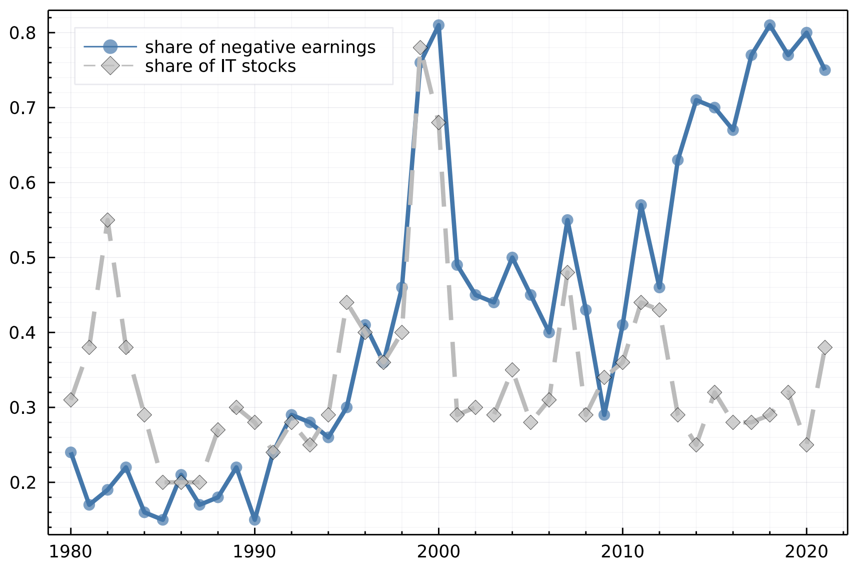
Notes: This figure presents the time-series plot of the fraction of unprofitable public firms. In each year, we count the number of firms with negative profits and divide it by the total number of firms. We use two different profitability measures – gross profits (Compustat data item *GP*) and net earnings (Compustat data item *NI*) – and two different aggregating approaches – weighted and unweighted. The weight is computed as the economy's output share of the industry that a firm belongs to. Data is obtained from *Compustat*.

Figure 2: Rise of Firms with Negative Net Earnings: Distributional Changes



Notes: This figure presents the distributional changes for companies with negative net earnings. In each year, we select all the firms with negative net income and then plot the size distribution. We use three different size-related indicators including market capitalization, total sales, and total assets. We choose 2019 instead of 2020 to avoid the possible unintended effects of pandemics. Data is obtained from *Compustat*. Earnings are deflated by using the annual national consumer price index (CPI) obtained from the U.S. Bureau of Labor Statistics (BLS).

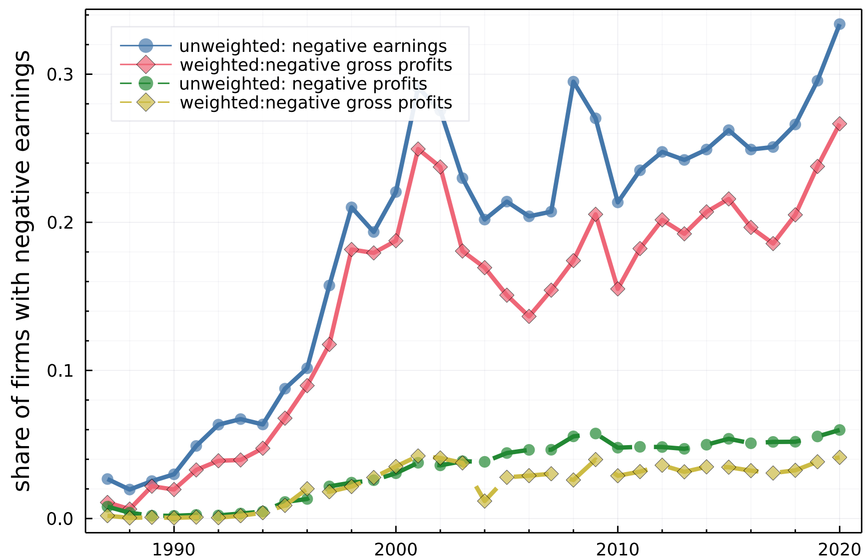
Figure 3: The Rise of IPOs with Negative Net Earnings



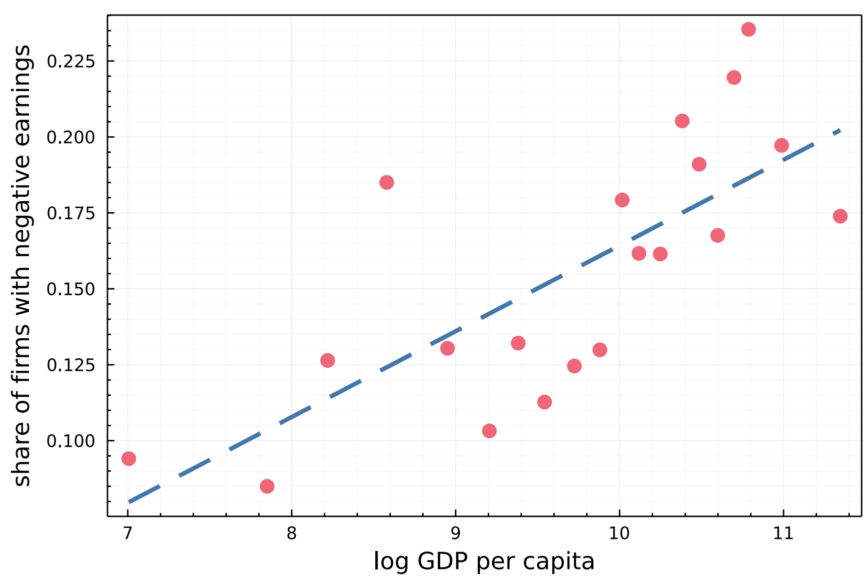
Notes: This figure presents the time-series plot of the fraction of unprofitable IPOs. In each year, we count the number of IPOs with negative net earnings and divide it by the total number of IPOs. The information related to corporate earnings is measured at the most recent twelve months before going public. The share of IT stocks is computed as the relative ratio of IT-related IPOs to total IPOs in each year. Data is obtained from Jay Ritter's personal website.

Figure 4: Global Evidence

(A) global rise of firms with negative net earnings



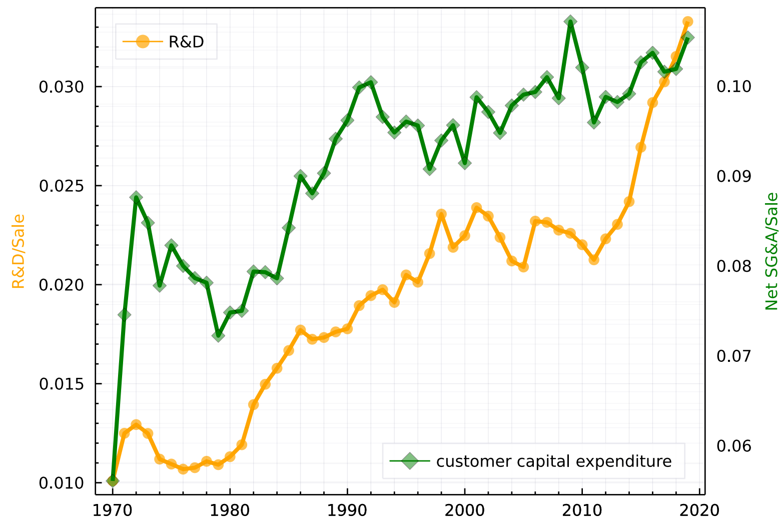
(B) cross-country heterogeneity



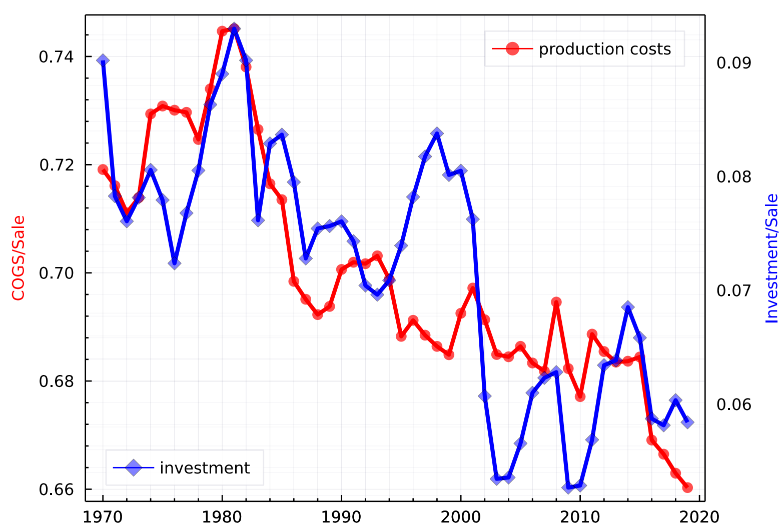
Notes: Graph (A) presents the time-series plot of the fraction of unprofitable public firms for a global dataset. In each year, for each country, we count the number of firms with negative profits and divide it by the total number of firms in that country. We use two different profitability measures – gross profits (Compustat data item *GP*) and net earnings (Compustat data item *NI*) – and two different aggregating approaches – weighted and unweighted. The weight is computed as the country's output share of the industry that a firm belongs to. Graph (B) presents the binscatter plot between the fraction of firms with negative net earnings and log real GDP per capita across different countries. Firm-level data is obtained from *Global Compustat*. Real GDP per capita is obtained from Penn World Table (PWT) and computed as output-side constant-price real GDP divided by total population.

Figure 5: Changing Business Model: Aggregate Levels

(A) increasing expenses on R&D and customer capital



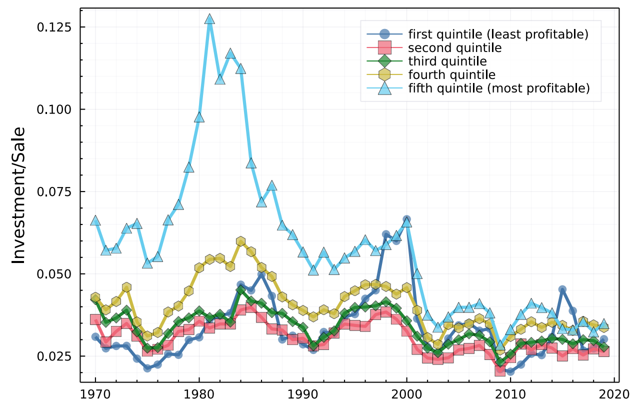
(B) decreasing expenses on production costs and investment



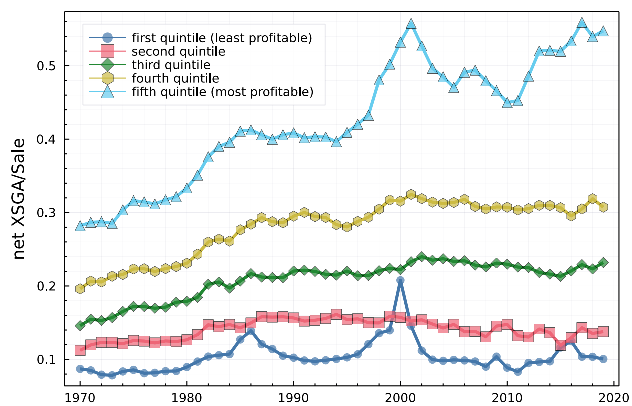
Notes: Graph (A) presents the time series plot of average R&D and customer capital expenses. Graph (B) plots the time series of average production costs and investment. All these four indicators are scaled by firm-level sales for better comparison. Data is obtained from *Compustat*.

Figure 6: Changing Business Model: Different Percentiles

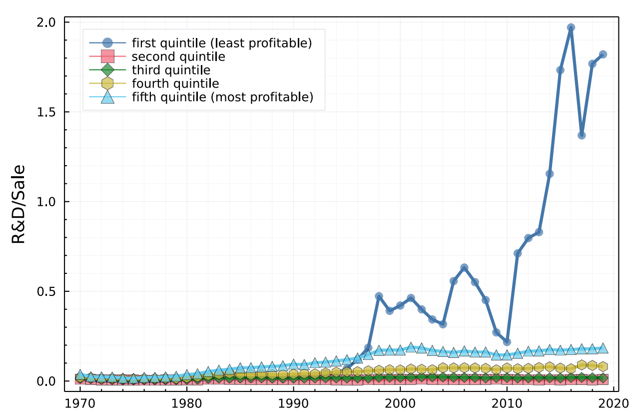
(A) investment



(B) customer capital expenses

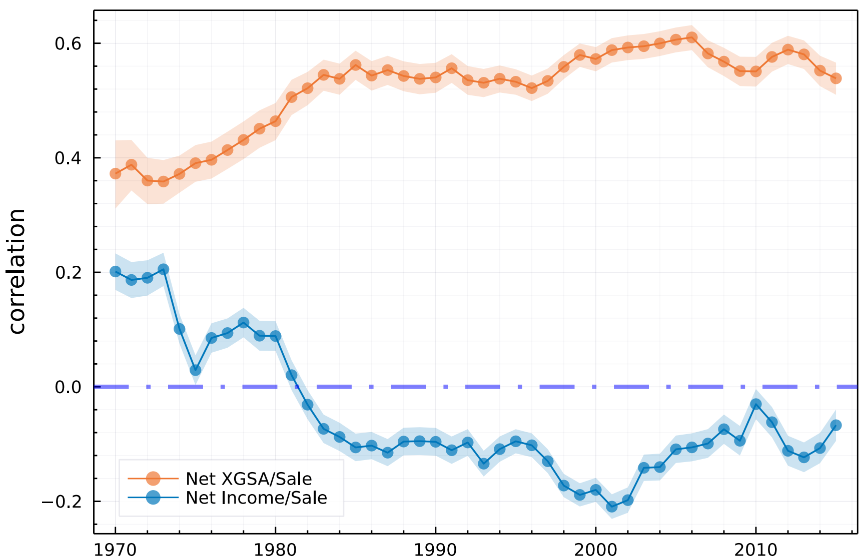


(C) R&D expenses



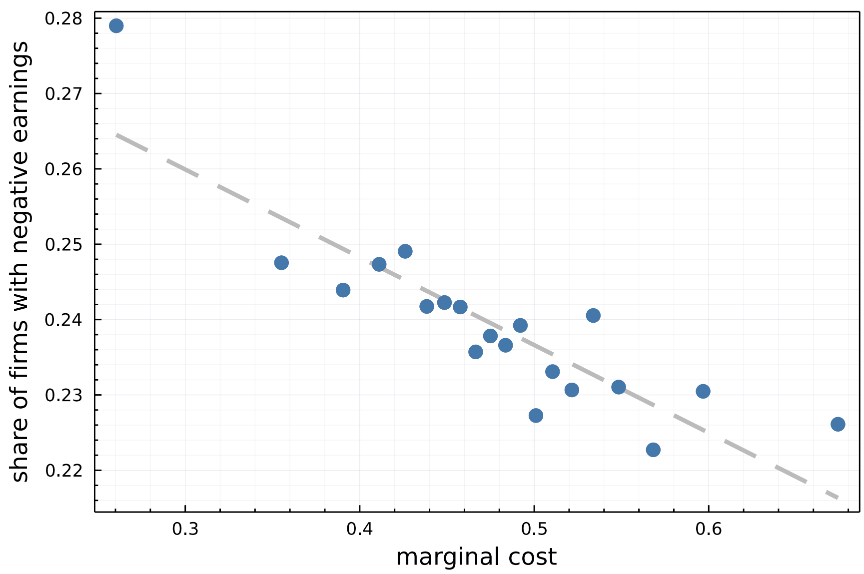
Notes: This figure presents the average investment, customer capital expenses, and R&D expenditures for firms with different gross profitability. In each year, we first classify firms into five different groups according to their gross profitability. After that, we compute the average ratios to sales of investment, customer capital expenses, and R&D expenditures, for each group of companies. Data is obtained from *Compustat*.

Figure 7: Time-varying Correlation between Markup and Net Earnings



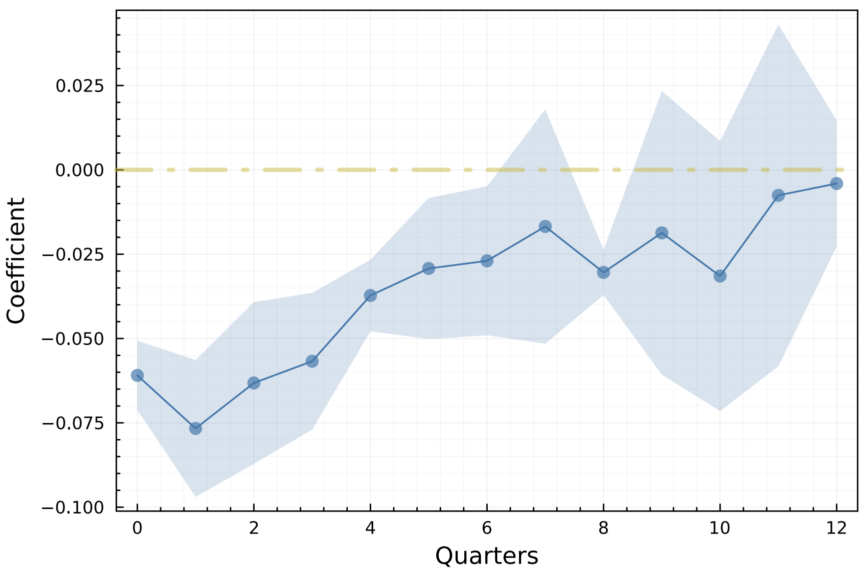
Notes: This orange line presents the annual cross-section correlation between markup and customer capital expenses, while the blue line shows the correlation between markup and net earnings. Both customer capital expenses and net earnings are scaled by sales. Firm-level markup is measured by following De Loecker, Eeckhout and Unger (2020)'s approach. Data is obtained from *Compustat*.

Figure 8: Binscatter Plot between Marginal Production Cost and Share of Firms with Negative Net Earnings



Notes: This figure presents the binscatter plot between industry-level marginal cost of production and share of firms with negative earnings. The gray dash line represents the linear-fit regression. Specifically, for each year and each industry at the 3-digit SIC level, we obtain the empirical measures on fixed production cost and operating scale by following De Ridder (2019)'s methodology. In addition, for each industry in each year, we count the number of firms with negative profits and divide it by the total number of firms to obtain the industry-level share of firms with negative net earnings. Data is obtained from *Compustat*.

Figure 9: Heterogeneous Effects of Monetary Policy Shocks on Customer Capital Expenses



Notes: This figure presents the estimated elasticity of firm customer capital expenses on interest rate shocks varies with corporate net earnings. All regressions control for both firm-by-quarter and industry-time fixed effects. The shaded area represents the 95% confidence interval. Standard errors are cluster by firm and quarter. Data is obtained from *Compustat*.

Tables

Table 1: Examples of Billion-Dollar Companies With Negative Net Earnings in 2019

Company name	Market capitalization	Net earnings
Zillow	9.59	-0.31
Pinterest	10.62	-1.36
Lyft	13.02	-2.60
Snap	23.12	-1.03
Spotify	27.57	-0.19
Uber	51.05	-8.51
Tesla	75.72	-0.86

Notes: Data is obtained from Yahoo Finance. All numbers are in billion U.S. dollars. We choose 2019 to avoid the impacts of the pandemic outbreak.

Table 2: Reduced-form Evidence: Markup and Customer Capital Expenditure

	markup											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
customer capital expenditure/sale (scaled by 100)	0.047***	0.046***	0.048***	0.048***	0.037***	0.042***	0.047***	0.057***	0.043***	0.037***	0.021**	0.021**
	(5.165)	(5.053)	(5.415)	(5.318)	(4.126)	(4.677)	(5.184)	(5.586)	(4.747)	(3.786)	(2.277)	(2.315)
return of assets		-0.003***								-0.001	-0.000	-0.001
		(-5.104)								(-1.409)	(-0.416)	(-0.700)
tangibility			0.555***							0.712***	0.871***	0.920***
			(59.534)							(61.671)	(77.100)	(81.964)
investment				0.301***						-0.059***	0.047*	0.027
				(20.242)						(-3.272)	(1.957)	(1.122)
size					-0.071***					-0.073***	-0.070***	-0.070***
					(-63.251)					(-54.909)	(-107.122)	(-108.396)
profitability						-0.005***				0.002*	0.002	0.002
						(-6.893)				(1.821)	(1.314)	(1.345)
book leverage							0.000			-0.002***	-0.002***	-0.002***
							(1.374)			(-5.751)	(-3.317)	(-3.758)
payout								0.028***		0.013	0.022*	0.013
								(3.301)		(1.484)	(1.907)	(1.151)
cash/asset									0.126***	0.297***	0.537***	0.526***
									(19.151)	(39.245)	(66.217)	(65.260)
log Tobin's q										-0.012***	0.037***	0.041***
										(-5.994)	(16.535)	(18.489)
	Fixed effects											
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Industry (sic3)											Yes	Yes
Industry $\times$ Year												Yes
N	126,837	126,832	126,832	125,315	126,832	126,628	125,318	115,334	126,824	97,526	98,823	98,823
Adjusted R^2	0.795	0.796	0.802	0.797	0.802	0.796	0.795	0.798	0.796	0.827	0.508	0.530

Notes: This table presents the association between markup and customer capital expenditure with different fixed-effect model specifications. The dependent variables are corporate markup, and we measure it by following De Loecker, Eeckhout and Unger (2020)'s method. Definitions of customer capital expenditure and all the other control variables are explained in Section 2.1. Data used in this table is at firm-year level, and obtained from *Compustat*. In columns (1)-(10), we introduce firm- and year-fixed effects. In column (11), we include industry- and year-fixed effect. In column (12), we use industry-, year-, and industry-year-fixed effects. T-statistics are in parentheses. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

Table 3: Reduced-form Evidence: Marginal Cost and Share of Firms with Negative Net Earnings

	share of firms with negative earnings			
	(1)	(2)	(3)	(4)
marginal cost	-0.304***	-0.098***	-0.575***	-0.115***
	(-23.413)	(-8.619)	(-31.726)	(-6.993)
intercept	0.384***	0.0598***	0.767***	0.357***
	(59.112)	(3.150)	(28.680)	(12.813)
	Fixed effects			
Year	No	Yes	No	Yes
Industry	No	No	Yes	Yes
N	13,769	13,769	13,769	13,769
Adjusted R^2	0.038	0.309	0.215	0.447

Notes: This table presents the association between industry-level marginal cost of production and share of firms with negative earnings with different fixed-effect model specifications. Specifically, for each year and each industry at the 3-digit SIC level, we obtain the empirical measures on fixed production cost and operating scale by following De Ridder (2019)'s methodology. In addition, for each industry in each year, we count the number of firms with negative profits and divide it by the total number of firms to obtain the industry-level share of firms with negative net earnings. Original data used in this table is at firm-year level, and obtained from *Compustat*. T-statistics are in parentheses. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the industry level.

Table 4: Time-series Correlation between the Share of Profitless firms and Nominal Interest Rates

	Federal Funds	3M	6M	1Y
Share of firms with negative net earnings	-0.2358*	-0.2621**	-0.3934***	-0.3940***
	(0.0547)	(0.0322)	(0.0014)	(0.0027)
	10Y	20Y	30Y	High Frequency
	-0.5597**	-0.6641***	-0.8272***	-0.5853***
	(0.0157)	(0.0036)	(0.0017)	(0.0067)

Notes: This figure presents the time-series correlation between the share of firms with negative net earnings and nominal interest rates. In each year, we count the number of firms with negative profits and divide it by the total number of firms. P-values are in parentheses. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Corporate net income data is obtained from *Compustat* dataset. Low-frequency nominal interest rate data is obtained from Fed St. Louis and high-frequency interest rate data is obtained from Nakamura and Steinsson (2018) and Acosta (2022).

Table 5: Monetary Policy and Customer Capital Expenses

	(1) Basic	(2) Baseline	(3) Level	(4) 3M	(5) 6M	(6) 1Y	(7) 10Y	(8) High MC	(9) Low MC	(10) High Frequency	(11) Quarterly
Negative × Δi	-0.146**	-0.182**		-0.340**	-0.307**	-0.230**	-0.192**	-0.172	-0.178**	-0.333*	-0.0416***
	(-2.304)	(-2.259)		(-2.124)	(-2.049)	(-2.068)	(-2.108)	(-1.369)	(-1.953)	(-1.714)	(-4.035)
Negative × i			-0.0642***								
			(-2.679)								
Lag term		-0.173***	-0.173***	-0.173***	-0.173***	-0.173***	-0.173***	-0.182***	-0.249***	-0.192***	0.0575*
		(-3.510)	(-3.511)	(-3.507)	(-3.507)	(-3.510)	(-3.510)	(-2.662)	(-3.555)	(-4.171)	(1.872)
Negative dummy		0.0251	0.393***	-0.0195	-0.0151	0.0202	0.0381	0.0818	-0.0188	0.0250	0.143***
		(0.362)	(2.998)	(-0.222)	(-0.174)	(0.291)	(0.542)	(0.637)	(-0.228)	(0.448)	(3.394)
Constant	1.052***	0.562	0.536	0.323	0.303	0.596	0.590	0.144	0.901**	0.718	0.0137
	(50.905)	(0.998)	(0.949)	(0.528)	(0.488)	(1.353)	(1.334)	(0.104)	(2.243)	(0.646)	(0.090)
Observations	129812	122894	122894	97589	97589	122227	122227	56464	66430	50574	198214
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.231	0.343	0.343	0.344	0.344	0.343	0.343	0.368	0.497	0.355	0.216

Notes: This table presents the association between customer capital expenditure and monetary policy with different fixed-effect model specifications. The left-hand-side variable $\frac{\text{net XGSA}_{i,t}}{\text{sale}_{i,t}}$ here represents our empirical proxy for firm's customer capital expenses. Negative$_{i,t}$ is the dummy equal to 1 when firm i has a negative net earning in year t. Δi_t represents the nominal interest rate changes during year $t-1$ to t. We also introduce the same set of firm-level control variables C that could affect companies' customer capital expenses as in Table 2. Data used in this table is at firm-year or firm-quarter level, and obtained from *Compustat*. Low-frequency nominal interest rate data is obtained from Fed St. Louis and high-frequency interest rate data is obtained from Nakamura and Steinsson (2018) and Acosta (2022). In all columns, we introduce firm- and year-fixed effects. T-statistics are in parentheses. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

Table 6: Single Sorting

Part I: Full Sample

(A) sorting variable: $\frac{NI}{GP}$

	value weighted					
	Low	2	3	4	High	Low - High
Raw excess return (%)	30.01	21.91	15.90	13.28	14.69	15.32***
(t-stat)						(5.35)
α^{CAPM} (%)	19.99	13.03	7.83	5.79	7.04	12.95***
(t-stat)						(5.63)
α^{FF5} (%)	21.68	10.96	7.34	5.98	8.13	13.55***
(t-stat)						(12.07)
α^{HXZ} (%)	24.68	13.80	8.00	4.87	7.39	17.29***
(t-stat)						(11.8)

(B) sorting variable: $\frac{\textbf{net XGSA}}{\textbf{GP}}$

	value weighted					
	Low	2	3	4	High	High - Low
Raw excess return (%)	13.84	14.50	16.46	20.55	37.68	23.84***
(t-stat)						(6.30)
α^{CAPM} (%)	6.69	6.10	7.89	13.15	27.02	20.33***
(t-stat)						(6.31)
α^{FF5} (%)	7.03	7.13	8.93	12.10	27.53	20.51***
(t-stat)						(11.02)
α^{HXZ} (%)	5.16	5.50	10.22	14.29	29.20	24.03***
(t-stat)						(11.04)

(C) sorting variable: $\frac{NI}{GP}$

	equal weighted					
	Low	2	3	4	High	Low - High
Raw excess return (%)	11.83	13.42	11.35	9.54	8.80	3.03*
(t-stat)						(1.79)
α^{CAPM} (%)	2.45	5.40	2.99	1.28	-0.21	2.66*
(t-stat)						(1.73)
α^{FF5} (%)	3.04	3.49	1.98	1.00	0.89	2.15**
(t-stat)						(1.98)
α^{HXZ} (%)	3.99	5.85	3.46	2.60	3.01	0.98
(t-stat)						(0.90)

(D) sorting variable: $\frac{\textbf{net XGSA}}{\textbf{GP}}$

	equal weighted					
	Low	2	3	4	High	High - Low
Raw excess return (%)	9.23	11.15	13.17	13.99	11.66	2.44
(t-stat)						(1.06)
α^{CAPM} (%)	0.41	2.53	4.83	5.98	2.69	2.28
(t-stat)						(1.07)
α^{FF5} (%)	3.09	3.54	4.12	4.81	3.62	0.53
(t-stat)						(0.35)
α^{HXZ} (%)	2.59	3.38	4.81	6.05	4.55	1.96
(t-stat)						(1.31)

Part II: Subsample Excluding Micro Cap Stocks

(E) sorting variable: $\frac{NI}{GP}$

	value weighted					
	Low	2	3	4	High	Low - High
Raw excess return (%)	25.41	20.05	14.89	13.12	14.43	10.98***
(t-stat)						(4.59)
α^{CAPM} (%)	15.97	11.08	6.72	5.81	6.75	9.22***
(t-stat)						(4.86)
α^{FF5} (%)	16.25	9.56	6.40	6.13	7.87	8.38***
(t-stat)						(8.30)
α^{HXZ} (%)	19.43	12.10	7.06	4.79	6.87	12.56***
(t-stat)						(10.0)

(F) sorting variable: $\frac{\textbf{net XGSA}}{\textbf{GP}}$

	value weighted					
	Low	2	3	4	High	High - Low
Raw excess return (%)	13.83	13.91	16.33	17.22	30.18	16.35***
(t-stat)						(5.32)
α^{CAPM} (%)	6.88	5.13	8.19	9.40	20.41	13.53***
(t-stat)						(5.22)
α^{FF5} (%)	6.95	6.80	8.54	9.42	19.11	12.16***
(t-stat)						(6.93)
α^{HXZ} (%)	5.28	4.84	9.05	10.78	22.64	17.37***
(t-stat)						(9.73)

(G) sorting variable: $\frac{NI}{GP}$

	equal weighted					
	Low	2	3	4	High	Low - High
Raw excess return (%)	8.83	11.62	9.84	8.94	7.37	1.46
(t-stat)						(0.92)
α^{CAPM} (%)	-0.74	3.22	1.48	0.61	-1.78	1.05
(t-stat)						(0.75)
α^{FF5} (%)	-0.23	2.17	0.87	0.62	-0.53	0.30
(t-stat)						(0.30)
α^{HXZ} (%)	2.19	4.31	2.72	1.94	1.84	0.35
(t-stat)						(0.35)

(H) sorting variable: $\frac{\textbf{net XGSA}}{\textbf{GP}}$

	equal weighted					
	Low	2	3	4	High	High - Low
Raw excess return (%)	8.70	10.48	11.57	12.24	8.39	-0.31
(t-stat)						(-0.15)
α^{CAPM} (%)	-0.22	1.64	3.02	3.93	-0.56	-0.34
(t-stat)						(-0.18)
α^{FF5} (%)	2.75	3.25	3.01	3.52	0.23	-2.52**
(t-stat)						(-1.83)
α^{HXZ} (%)	2.13	2.72	4.01	4.81	2.18	0.05
(t-stat)						(0.04)

Notes: This table reports the average equal- and value-weighted excess stock returns of 5 portfolios one-way sorted on the relative ratios of net earnings (*NI*) or customer capital expenses (*net XGSA*) to gross profitability (*GP*). Definitions of these variables are as in Section 2.1. The excess return is the average annualized portfolio excess stock return in percentage points. *t*-stats are heteroscedasticity and autocorrelation consistent t-statistics (i.e., Newey-West). Part I reports the value- and equal-weighted returns across the full sample, meanwhile Part II presents the corresponding outcomes in a subsample excluding micro cap stocks. The micro cap firms are defined as firms with a market capitalization lower than the bottom 20th percentile of all NYSE firms. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. The sample period is from July 1970 to June 2019. Data is obtained from *CRSP* and *Compustat*.

Table 7: Double Sorting: Value-Weighted Returns

Part I: Full Sample with Net Income ($\frac{NI}{GP}$) + Gross Profitability ($\frac{GP}{AT}$)

(A): Raw excess return (%)								
		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	34.17	28.74	29.75	32.11	41.50	7.32*	(1.81)
	2	21.88	21.49	19.62	20.80	26.79	4.91*	(1.63)
Net Income	3	15.34	13.33	13.37	15.65	20.39	5.05**	(2.12)
	4	34.20	12.58	12.08	13.18	15.11	-19.09***	(-4.58)
	High	25.96	11.69	12.78	14.32	13.41	-12.54***	(-3.29)
	Low - High	8.20***	17.02***	16.97***	17.79***	28.09***	15.56***	(4.26)
	(t-stat)	(2.29)	(4.44)	(5.08)	(5.28)	(6.42)	(4.26)	
(B): α^{CAPM} (%)								
		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	22.53	19.30	20.56	21.36	31.35	8.83***	(2.26)
	2	11.37	11.38	12.77	11.27	17.75	6.38***	(2.29)
Net Income	3	6.54	5.77	5.47	7.73	11.99	5.46***	(2.47)
	4	21.87	5.13	4.77	6.22	6.47	-15.4***	(4.05)
	High	16.32	3.81	6.19	6.10	5.39	-10.93***	(3.39)
	Low - High	6.21*	15.49***	14.37***	15.26***	25.96***	15.04***	(4.21)
	(t-stat)	(1.83)	(4.70)	(5.11)	(4.95)	(6.69)	(4.21)	
(C): α^{FF5} (%)								
		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	27.59	19.26	20.38	18.99	25.16	-2.42	(-0.75)
	2	14.03	12.34	11.40	10.33	18.50	4.46***	(2.04)
Net Income	3	8.71	3.38	6.46	7.22	8.59	-0.12	(-0.07)
	4	23.42	4.27	5.17	6.23	8.89	-14.53***	(-6.06)
	High	23.68	2.93	5.21	9.70	6.67	-17.01***	(-7.67)
	Low - High	3.91	16.33***	15.17***	9.28***	18.49***	1.48	(0.49)
	(t-stat)	(1.42)	(7.43)	(8.61)	(4.69)	(7.61)	(0.49)	
(D): α^{HXZ} (%)								
		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	28.17	27.04	19.04	15.56	30.03	1.86	(0.59)
	2	18.15	16.37	14.05	12.23	18.16	0.01	(0.01)
Net Income	3	9.15	7.77	6.90	7.66	8.81	0.34	(0.20)
	4	24.40	4.46	5.60	5.45	5.53	-18.87***	(-7.32)
	High	25.15	5.75	4.96	5.65	5.07	-20.09***	(-7.95)
	Low - High	3.02	21.29***	14.08***	9.91***	24.97***	4.88*	(1.65)
	(t-stat)	(1.09)	(8.86)	(7.36)	(4.61)	(8.87)	(1.65)	

Part II: Full Sample with Customer Capital Expenses ($\frac{\text{net XGSA}}{GP}$) + Gross Profitability ($\frac{\text{GP}}{AT}$)

(E): Raw Excess return (%)

		Gross Profitability						
		Low	2	3	4	High	Low-High	(t-stat)
	Low	13.29	13.19	14.52	13.69	15.45	2.16	(0.58)
	2	10.86	15.04	12.88	14.29	16.46	5.60**	(2.38)
Customer Capital Expenses	3	19.16	17.35	14.25	16.32	16.56	-2.59	(0.88)
	4	30.55	19.98	20.24	16.86	31.96	1.4	(0.35)
	High	34.55	37.88	41.54	32.97	40.30	5.75	(1.31)
	High - Low	21.25***	24.70***	27.02***	19.28***	24.84***	27.00***	(6.33)
	(t-stat)	(4.46)	(5.22)	(5.76)	(4.90)	(5.44)	(6.33)	

(F): α^{CAPM} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	5.81	6.47	6.34	6.11	6.65	0.83	(0.27)
	2	2.63	6.56	5.72	6.34	7.64	5.01***	(2.28)
Customer Capital Expenses	3	10.78	9.49	7.26	8.13	9.15	-1.64	(-0.66)
	4	18.50	12.24	13.22	8.29	23.50	5.00	(1.39)
	High	24.32	27.82	30.85	22.31	32.23	7.91*	(1.87)
	High - Low	18.51	21.35	24.51	16.21	25.58	26.42***	(6.37)
	(t-stat)	(4.04)	(5.19)	(5.76)	(4.54)	(6.30)	(6.37)	

(G): α^{FF5} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	4.37	3.33	8.48	11.17	8.29	3.92*	(1.82)
	2	2.44	7.48	7.43	6.08	10.04	7.60***	(4.62)
Customer Capital Expenses	3	15.04	10.62	6.85	8.49	8.01	-7.03***	(-3.99)
	4	20.17	12.07	9.74	9.21	17.42	-2.75	(-0.95)
	High	27.50	31.19	24.68	13.05	26.02	-1.49	(-0.42)
	High - Low	23.14	27.86	16.20	1.87	17.73***	21.65***	(7.13)
	(t-stat)	(6.97)	(10.08)	(5.73)	(0.73)	(6.37)	(7.13)	

(H): α^{HXZ} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	12.71	3.52	5.71	3.58	4.94	-7.77***	(-3.20)
	2	4.82	8.43	7.16	6.30	5.77	0.95	(0.58)
Customer Capital Expenses	3	17.52	12.65	7.87	11.19	8.60	-8.92***	(-4.69)
	4	25.14	13.19	13.14	9.09	23.56	-1.59	(-0.53)
	High	24.45	29.32	29.24	20.09	31.69	7.24***	(2.05)
	High - Low	11.74***	25.80***	23.53***	16.51***	26.75***	18.98***	(5.89)
	(t-stat)	(3.34)	(7.96)	(7.64)	(6.79)	(8.89)	(5.89)	

Part III: Subsample Excluding Micro Cap Stocks with Net Income ($\frac{NI}{GP}$) + Gross Profitability ($\frac{GP}{AT}$)

(I): Raw excess return (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	28.83	26.75	24.70	23.54	34.54	5.70*	(1.62)
	2	19.48	17.95	19.02	18.22	22.58	3.11	(1.01)
Net Income	3	12.54	13.14	13.63	14.49	17.96	5.42***	(2.62)
	4	29.85	12.35	12.21	13.15	13.95	-15.89***	(-3.72)
	High	25.61	11.73	12.30	13.79	13.62	-11.99***	(-3.48)
	Low - High	3.22	15.02***	12.39***	9.75***	20.91***	8.92***	(2.82)
	(t-stat)	(0.97)	(4.34)	(4.05)	(3.54)	(6.32)	(2.82)	

(J): α^{CAPM} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	16.56	18.17	16.42	12.85	24.73	8.17***	(2.41)
	2	10.35	7.86	12.06	9.61	14.05	3.70	(1.36)
Net Income	3	4.37	5.66	5.84	6.41	9.17	4.80***	(2.47)
	4	19.31	4.57	4.98	6.14	5.15	-14.16***	(-3.61)
	High	15.48	3.87	5.80	5.88	5.55	-9.93***	(-3.33)
	Low - High	1.07	14.3***	10.63***	6.97***	19.18***	9.24***	(3.00)
	(t-stat)	(0.34)	(5.05)	(4.04)	(2.75)	(6.54)	(3.00)	

(K): α^{FF5} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	22.33	18.56	15.55	14.53	20.80	-1.53	(-0.56)
	2	11.66	8.73	12.61	8.35	12.08	0.42	(0.20)
Net Income	3	6.21	2.91	7.13	5.01	6.80	0.59	(0.40)
	4	15.41	3.22	5.29	6.42	8.18	-7.24***	(-3.05)
	High	21.61	3.06	5.27	9.64	6.43	-15.18***	(-7.48)
	Low - High	0.72	15.50***	10.28***	4.89***	14.37***	0.81	(0.31)
	(t-stat)	(0.29)	(7.42)	(5.70)	(2.77)	(6.76)	(0.31)	

(L): α^{HXZ} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	23.98	22.74	17.20	13.69	24.18	0.20	(0.07)
	2	16.30	12.69	13.70	10.53	13.05	-3.25***	(-1.69)
Net Income	3	7.06	6.29	7.94	6.36	6.80	-0.26	(0.17)
	4	20.97	3.57	5.08	5.59	4.11	-16.86***	(-6.52)
	High	22.66	5.63	4.54	4.59	5.35	-17.31***	(-7.69)
	Low - High	1.31	17.12***	12.66***	9.11***	18.82***	1.51	(0.57)
	(t-stat)	(0.51)	(7.79)	(7.37)	(5.41)	(9.01)	(0.57)	

Part IV: Subsample Excluding Micro Cap Stocks with Customer Capital Expenses ($\frac{\text{net XGSA}}{GP}$) + Gross Profitability ($\frac{\text{GP}}{AT}$)

(M): Raw excess return (%)

		Gross Profitability						
		Low	2	3	4	High	Low-High	(t-stat)
	Low	11.31	13.26	14.89	13.55	14.59	3.28	(1.03)
	2	11.12	13.65	12.92	14.31	16.47	5.35**	(2.12)
Customer Capital Expenses	3	17.60	17.53	13.57	16.21	15.46	-2.14	(0.75)
	4	27.62	18.72	16.69	14.20	19.28	-8.34**	(-2.09)
	High	31.49	31.65	29.11	24.86	38.58	7.08	(1.55)
	High - Low	20.19***	18.39***	14.22***	11.31***	23.99***	27.27***	(6.93)
	(t-stat)	(4.27)	(4.50)	(4.15)	(4.00)	(6.15)	(6.93)	

(N): α^{CAPM} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	4.28	6.46	6.80	6.03	5.35	1.07	(0.40)
	2	2.82	5.60	5.16	7.17	7.79	4.97**	(2.13)
Customer Capital Expenses	3	9.74	9.64	6.36	7.22	7.87	-1.87	(-0.76)
	4	15.89	10.97	9.88	5.80	11.25	-4.65	(1.38)
	High	20.55	22.37	20.22	15.33	29.13	8.58**	(1.96)
	High - Low	16.27***	15.91***	13.42***	9.30***	23.77***	24.85***	(6.66)
	(t-stat)	(3.62)	(4.51)	(4.22)	(3.53)	(6.86)	(6.66)	

(O): α^{FF5} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	3.94	2.95	9.63	11.08	6.83	2.89	(1.41)
	2	2.94	6.04	6.01	7.73	10.97	8.03***	(4.77)
Customer Capital Expenses	3	14.44	10.79	6.14	7.15	8.37	-6.07***	(-3.21)
	4	22.37	11.71	8.99	6.08	10.93	-11.44***	(-4.36)
	High	25.35	25.51	18.10	11.31	20.37	-4.98	(-1.40)
	High - Low	21.42***	22.56***	8.47***	0.23	13.54***	16.44***	(5.67)
	(t-stat)	(6.97)	(9.84)	(3.75)	(0.12)	(5.14)	(5.67)	

(P): α^{HXZ} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	9.97	3.52	6.05	3.38	4.17	-5.79***	(-2.95)
	2	5.26	6.45	6.31	6.22	6.41	1.16	(0.68)
Customer Capital Expenses	3	17.22	12.08	9.31	7.87	7.65	-9.57***	(-4.94)
	4	22.41	15.78	12.12	6.42	11.78	-10.63***	(-4.04)
	High	24.04	23.88	21.52	16.02	26.90	2.86	(0.86)
	High - Low	14.07***	20.36***	15.48***	12.63***	22.72***	16.93***	(6.13)
	(t-stat)	(4.41)	(7.96)	(6.88)	(6.89)	(9.09)	(6.13)	

Notes: This table reports the average value-weighted excess stock returns of 25 portfolios two-way sorted on net earnings ($\frac{\text{NI}}{GP}$)/customer capital expenses ($\frac{\text{net XGSA}}{GP}$) and gross profitability ($\frac{\text{GP}}{AT}$). Definitions of these variables are as in Section 2.1. The raw excess return is the average annualized portfolio excess stock return. α^{CAPM}, α^{FF5}, and α^{HXZ} are portfolio average abnormal returns, obtained as the intercept from monthly CAPM, Fama and French (2015) five-factor model, and Hou, Xue and Zhang (2008) q-factor model regressions, respectively. All of them are reported in annual percentages. t-stats are heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). Part I and II report the results for the full sample, meanwhile Part III and IV present the corresponding outcomes in a subsample excluding micro cap stocks. The micro cap firms are defined as firms with a market capitalization lower than the bottom 20th percentile of all NYSE firms. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. The sample period is from July 1970 to June 2019. Data is obtained from *CRSP* and *Compustat*.

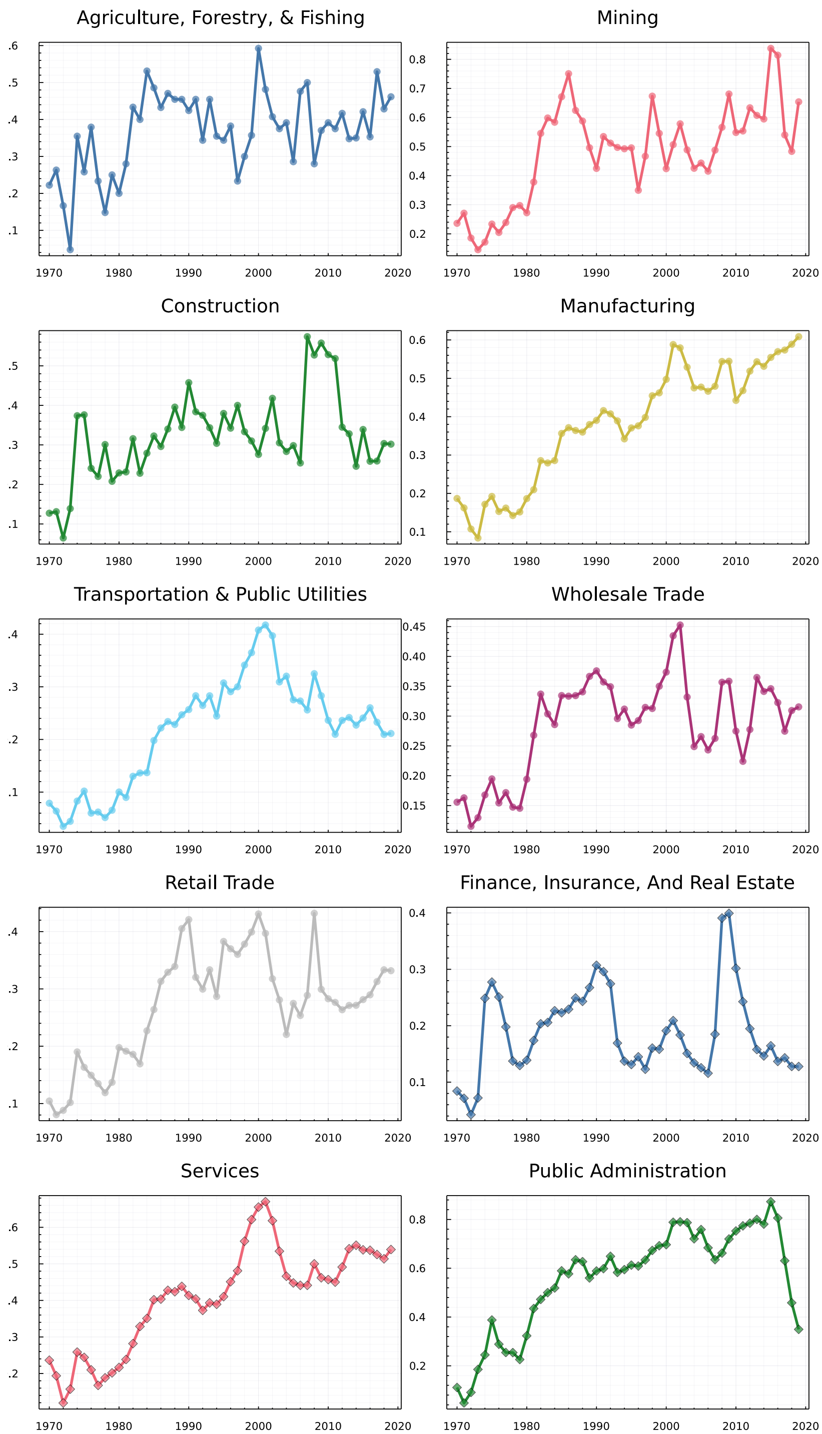
Table 8: Fama-MacBeth Regressions of Future Returns on Net Income and Customer Capital Expenses

	(1) Full	(2) NI<0	(3) NI≥0	(4) Full	(5) NI<0	(6) NI≥0	(7) Full	(8) NI<0	(9) NI≥0
Net Income (Loss)	0.341***	-5.758***	0.237***				0.178**	-8.584**	0.138
	(3.734)	(-2.694)	(2.814)				(2.153)	(-2.310)	(1.610)
Customer Capital Expenses				0.144***	1.359**	0.0957**	0.0754*	0.646	0.0364
				(3.034)	(2.016)	(2.320)	(1.691)	(0.923)	(0.879)
Gross Profitability	0.397***	0.303*	0.493***	0.779***	1.169***	0.447***	0.787***	1.223***	0.454***
	(2.879)	(1.825)	(3.669)	(5.001)	(4.812)	(3.085)	(5.071)	(5.016)	(3.159)
Size	-0.155***	-0.343***	-0.0964***	-0.144***	-0.286***	-0.102***	-0.146***	-0.311***	-0.103***
	(-3.602)	(-5.481)	(-2.780)	(-3.051)	(-3.808)	(-2.674)	(-3.060)	(-4.036)	(-2.649)
Book-to-Market	0.0264	0.00194	0.0635**	0.0694***	0.0664**	0.0813**	0.0708***	0.0610**	0.0816**
	(1.492)	(0.105)	(2.329)	(2.608)	(2.234)	(2.154)	(2.654)	(2.034)	(2.163)
Momentum	-4.483**	-12.16***	-0.274	-5.232***	-12.89***	-1.046	-5.240***	-13.02***	-1.047
	(-2.461)	(-6.109)	(-0.139)	(-2.883)	(-6.408)	(-0.528)	(-2.889)	(-6.464)	(-0.528)
Constant	1.770***	2.344***	1.320***	1.562***	1.878***	1.427***	1.564***	1.919***	1.429***
	(3.947)	(4.490)	(3.722)	(3.187)	(3.373)	(3.543)	(3.187)	(3.418)	(3.528)
# of Observations	1853306	579997	1273309	1033675	323904	709771	1033663	323904	709759
Adj. R^2	0.025	0.026	0.030	0.028	0.034	0.034	0.028	0.036	0.035

Notes: This table reports the estimated coefficients from Fama-MacBeth regressions of monthly stock returns on net income, customer capital expenses, size, book-to-market ratio, and momentum. Definitions of these variables except for momentum are as in Section 2.1, and for better illustration, both net income and customer capital expenses are measured in million US dollars. Momentum is measured as the average stock return between the past 12 to past 1 month. T-statistics are in parentheses. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. The sample period is from July 1970 to June 2019. Data is obtained from *CRSP* and *Compustat*.

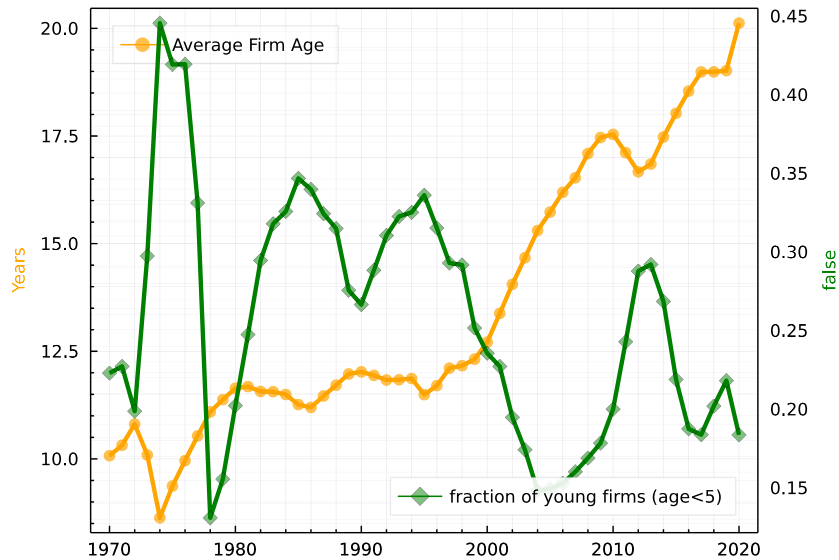
Online Appendix

Figure A1: The Rise of Firms with Negative Net Earnings: Ten Different Industries



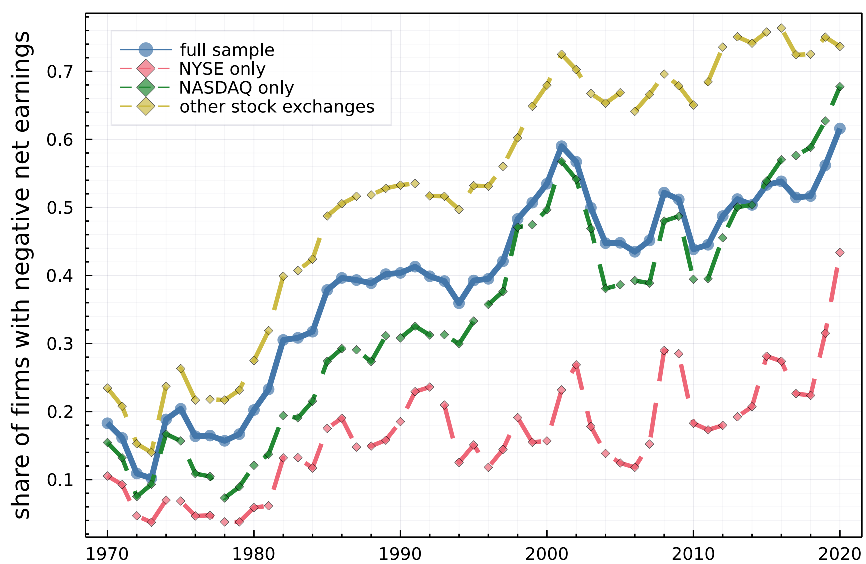
Notes: This figure presents the time-series plot of the fraction of unprofitable public firms in different industries. In each year, for each industry we count the number of firms with negative net earnings and divide it by the total number of firms. Ten industries are defined as follows: Agriculture, Forestry, & Fishing (SIC 01-09); Mining (SIC 10-14); Construction (SIC 15-17); Manufacturing (SIC 20-39); Transportation & Public Utilities (SIC 40-49); Wholesale Trade (SIC 50-51); Retail Trade (SIC 52-59); Finance, Insurance, & Real Estate (SIC 60-67); Services (SIC 70-89); and Public Administration (SIC 90-99). Data is obtained from *Compustat*.

Figure A2: Average Firm Age



Notes: This figure presents the time-series plot of average age for public companies in the US. A firm's age is defined as the year difference between the current year and the year that a certain firm first appears in the *Compustat* dataset. The fraction of young firms is computed as follows. For each year, we count the number of firms with a age less than 5 and divide it by the total number of firms. Data is obtained from *Compustat*.

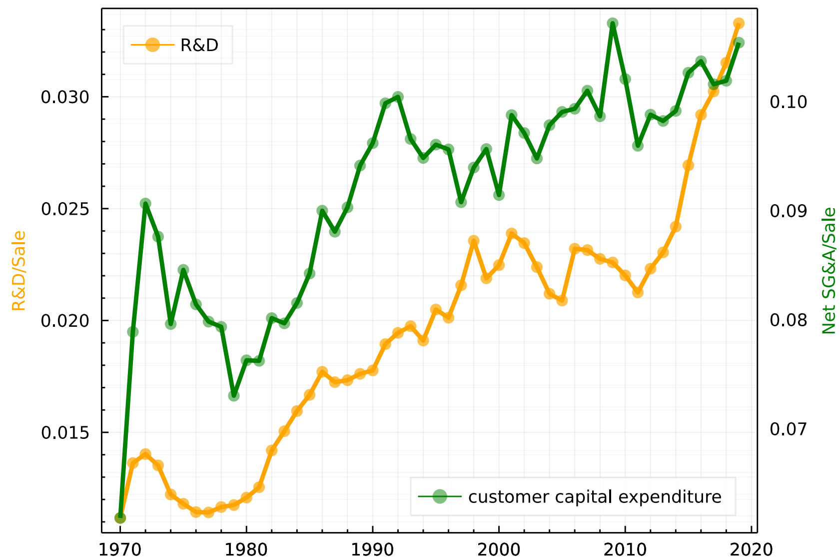
Figure A3: The Rise of Firms with Negative Net Earnings: Different Stock Exchanges



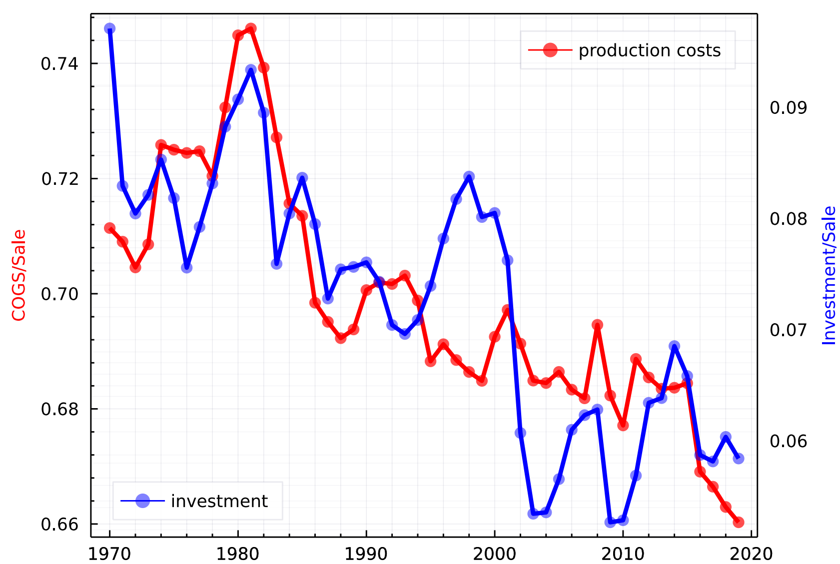
Notes: This figure presents the time-series plot of the fraction of unprofitable public firms in different stock exchanges. In each year, for each stock exchange, we count the number of firms with negative net earnings and divide it by the total number of firms in that exchange. Data is obtained from *Compustat*.

Figure A4: Changing Business Model: Weighted by 3-digit Industry Sale Share

(A) R&D and customer capital expenses



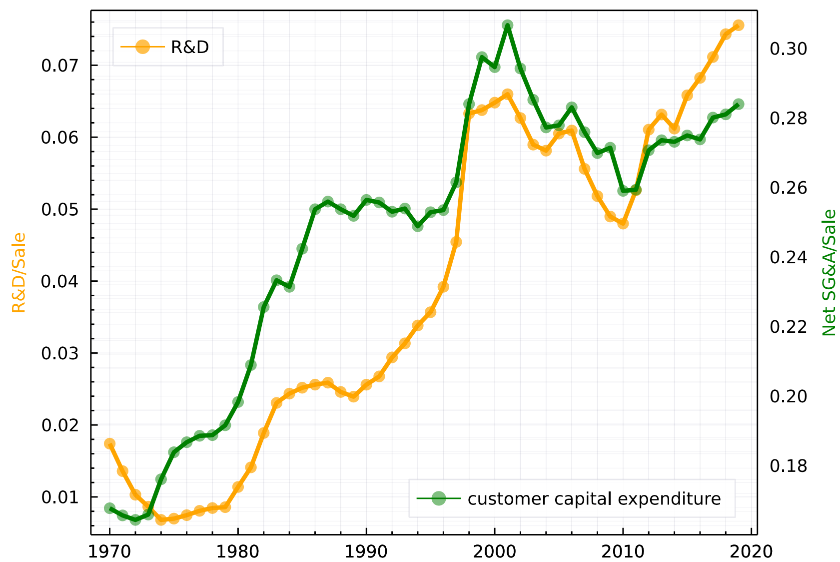
(B) production costs and investment



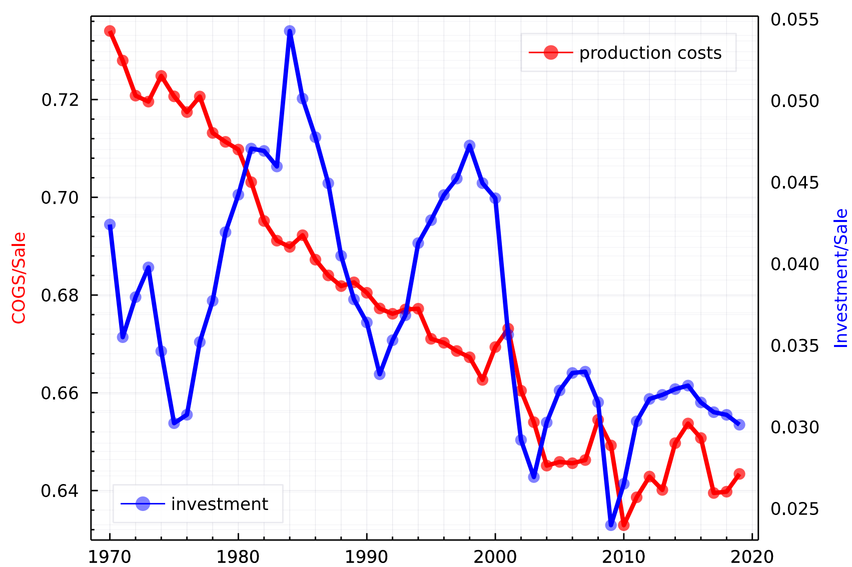
Notes: Graph (A) presents the time series plot of weighted-average R&D and customer capital expenses. Graph (B) plots the time series of weighted-average production costs and investment. All these four indicators are scaled by firm-level sales for better comparison. The weight is computed as the economy's output share of the 3-digit industry that a firm belongs to. The Data is obtained from *Compustat*.

Figure A5: Changing Business Model: Median Average

(A) R&D and customer capital expenses

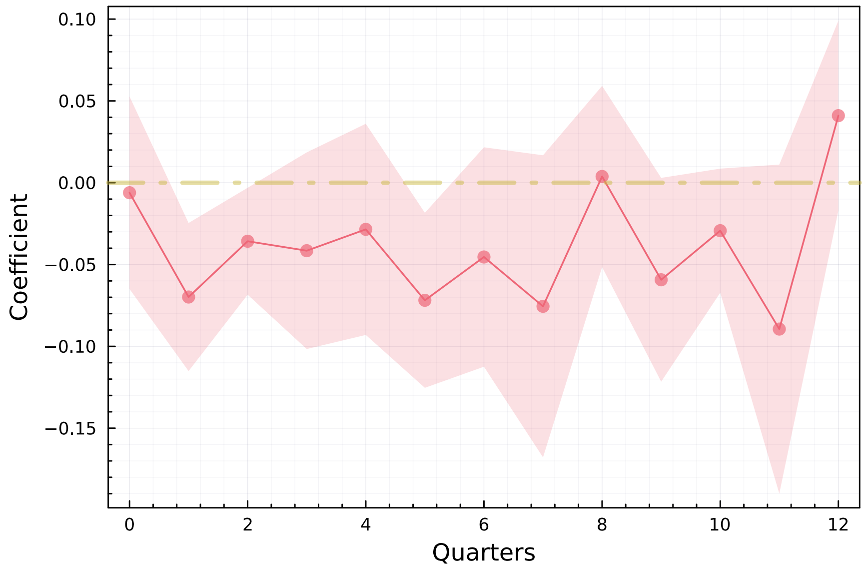


(B) production costs and investment



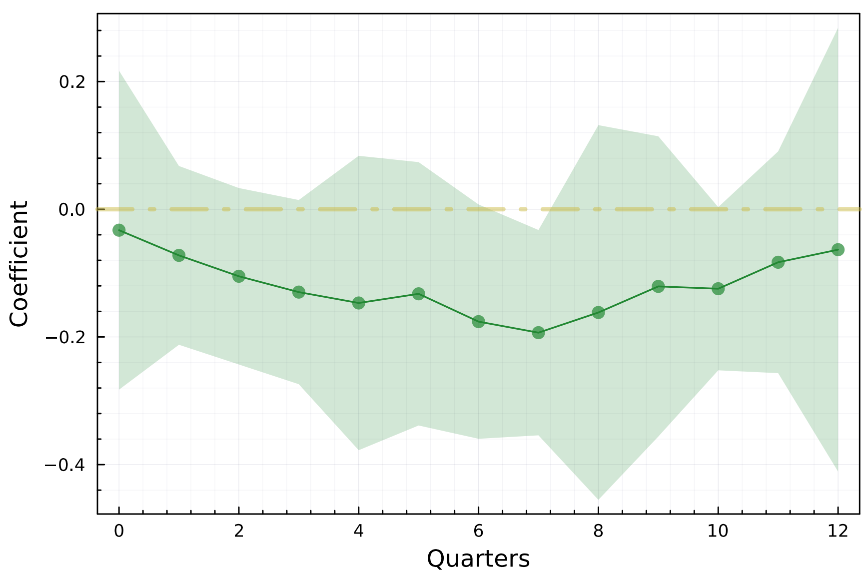
Notes: Graph (A) presents the time series plot of median-average R&D and customer capital expenses. Graph (B) plots the time series of median-average production costs and investment. All these four indicators are scaled by firm-level sales for better comparison. The Data is obtained from *Compustat*.

Figure A6: Heterogeneous Effects of Monetary Policy Shocks on R&D



Notes: This figure presents the estimated elasticity of firm R&D expenses on interest rate shocks varies with corporate net earnings. All regressions control for both firm-by-quarter and industry-time fixed effects. The shaded area represents the 95% confidence interval. Standard errors are cluster by firm and quarter. Data is obtained from *Compustat*.

Figure A7: Heterogeneous Effects of Monetary Policy Shocks on Investment



Notes: This figure presents the estimated elasticity of corporate investment on interest rate shocks varies with corporate net earnings. All regressions control for both firm-by-quarter and industry-time fixed effects. The shaded area represents the 95% confidence interval. Standard errors are cluster by firm and quarter. Data is obtained from *Compustat*.

Table A1: Top 50 Companies with Negative Net Earnings in 2019

Company Name	Net Earnings (in million US dollars)	Market Capitalization (in million US dollars)	Industry
Boeing Co	-636	183373.2	Manufacturing
Vanjia Corp	-0.041	122949	Construction
General Electric Co	-4979	97520.92	Public Administration
Altria Group Inc	-1293	92731.88	Manufacturing
Tesla Inc	-862	75717.73	Manufacturing
Uber Technologies Inc	-8506	51054.09	Transportation and Public Utilities
Dun & Bradstreet Corp	-560	45586.05	Services
Workday Inc	-480.674	42780.25	Services
Dow Inc	-1359	40582.24	Manufacturing
Occidental Petroleum Corp	-667	36846.36	Mining
Constellation Brands Inc	-11.8	32946.64	Manufacturing
MercadoLibre Inc	-171.999	28431.14	Services
Splunk Inc	-336.668	24498.16	Services
Snap Inc	-1033.66	23119.95	Services
Weyerhaeuser Co	-76	22508.06	Manufacturing
Corteva Inc	-959	22127.94	Agriculture, Forestry and Fishing
Palo Alto Networks Inc	-81.9	21929.07	Services
Halliburton Co	-1131	21484.66	Mining
Hess Corp	-408	20374.04	Mining
Seagen Inc	-158.65	19652.04	Manufacturing
Freeport-McMoRan Inc	-239	19037.12	Mining
Concho Resources Inc	-705	17311.63	Mining
Equifax Inc.	-398.8	16982.54	Services
Roku Inc	-59.937	16054.21	Manufacturing
OKTA INC	-208.913	15703.8	Services
Live Nation Entertainment Inc	-4.882	15273.85	Services
Biomarin Pharmaceutical Inc	-23.848	15205.3	Manufacturing
RingCentral Inc	-53.607	14664.17	Services
Lumen Technologies Inc	-5269	14399.67	Transportation and Public Utilities
DocuSign Inc.	-208.359	14230.25	Services
Western Digital Corp	-754	14027.25	Manufacturing
Exact Sciences Corporation	-83.993	13652.45	Services
Twilio Inc	-307.063	13603.23	Services
Hologic Inc	-203.6	13515.42	Manufacturing
Annaly Capital Management Inc	-2162.865	13471.6	Finance, Insurance and Real Estate
Icahn Enterprises LP	-1098	13165.86	Public Administration
Lyft Inc	-2602.241	13017.68	Transportation and Public Utilities
CrowdStrike Holdings Inc	-141.779	13008.99	Services
Alnylam Pharmaceuticals Inc	-886.116	12920.69	Manufacturing
Noble Energy Inc	-1512	12045.76	Mining
Slack Technologies Inc	-571.058	11512.61	Services
Equitable Holdings Inc	-1733	11490.76	Finance, Insurance and Real Estate
Datadog Inc	-16.71	11197.5	Services
Zscaler Inc	-28.655	10723.61	Services
Formula One Group - The Liberty Media Group	-311	10647.7	Services
Chewy Inc	-252.37	10640.27	Retail Trade
Pinterest Inc	-1361.371	10623.01	Services
Coupa Software Inc	-90.832	10398.85	Services
Coty Inc	-3784.2	10106.28	Manufacturing
Darden Restaurants Inc	-52.4	9983.653	Retail Trade

Table A2: Monetary Policy and Other Expenses

(A) capital investment

capital investment	(1) Basic	(2) Baseline	(3) Level	(4) 3M	(5) 6M	(6) 1Y	(7) 10Y	(8) High MC	(9) Low MC	(10) High Frequency	(11) Quarterly
Negative × Δi	-0.00205	-0.00255		-0.00325	-0.00271	-0.00196	0.000164	-0.00426	-0.00152	-0.00468	-0.00661***
	(-0.992)	(-1.256)		(-1.124)	(-1.110)	(-1.149)	(0.124)	(-1.254)	(-0.541)	(-1.188)	(-4.345)
Negative × i			-0.000988								
			(-0.848)								
Lag term		-0.0612***	-0.0612***	-0.0612***	-0.0612***	-0.0613***	-0.0613***	-0.0616***	-0.0924	-0.253 ***	-0.0277*
		(-8.293)	(-8.299)	(-8.320)	(-8.319)	(-8.250)	(-8.250)	(-8.230)	(4.169)	(-44.865)	(-1.855)
Negative dummy		-0.00606***	-0.000361	-0.00425**	-0.00414**	-0.00578***	-0.00528**	-0.00759***	-0.00422***	-0.00634*	-0.00134
		(0.000)	(0.963)	(0.013)	(0.020)	(0.001)	(0.012)	(0.003)	(0.000)	(0.060)	(-0.516)
Constant	0.0871***	0.0952***	0.0951***	0.0898***	0.0897***	0.0948***	0.0947***	0.0939***	0.109***	0.0757***	0.0446***
	(25.208)	(18.911)	(18.816)	(15.716)	(15.583)	(22.872)	(22.777)	(18.533)	(3.967)	(10.111)	(10.058)
Observations	311705	304701	304701	227953	227953	300156	300156	185800	118901	117453	591865
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.108	0.117	0.117	0.115	0.115	0.117	0.117	0.117	0.654	0.287	0.0513

(B) R&D investment

R&D investment	(1) Basic	(2) Baseline	(3) Level	(4) 3M	(5) 6M	(6) 1Y	(7) 10Y	(8) High MC	(9) Low MC	(10) High Frequency	(11) Quarterly
Negative × Δi	-0.0181	-0.0137		-0.0256	-0.0225	-0.0154	-0.0229	-0.0138	0.00458	-0.0197	-0.00919
	(-1.453)	(-1.353)		(-1.441)	(-1.340)	(-1.255)	(-1.214)	(-1.342)	(0.297)	(-0.531)	(-1.270)
Negative × i			-0.00103								
			(-0.259)								
Lag term		0.367**	0.367**	0.367**	0.367**	0.367**	0.367**	0.376**	0.00179	0.364**	-0.0450**
		(2.300)	(2.300)	(2.299)	(2.299)	(2.300)	(2.300)	(2.392)	(0.092)	(2.239)	(-2.330)
Negative dummy		0.0181*	0.0271	0.0203	0.0208	0.0183	0.0175	0.0182*	-0.0219	0.0188	0.0485
		(1.667)	(1.290)	(1.495)	(1.529)	(1.634)	(1.449)	(1.646)	(-1.299)	(1.063)	(1.682)
Constant	0.210***	0.251***	0.249***	0.258***	0.257***	0.222***	0.222***	0.255***	0.272***	0.448**	0.223
	(35.042)	(3.037)	(3.025)	(3.029)	(3.014)	(3.330)	(3.323)	(2.986)	(2.895)	(2.455)	(1.559)
Observations	147679	141836	141836	113768	113768	141101	141101	67414	74422	59496	238234
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.108	0.117	0.117	0.115	0.115	0.117	0.117	0.099	0.772	0.378	0.0735

Notes: This table presents the association between customer capital expenditure and monetary policy with different fixed-effect model specifications. In Panel (A), the left-hand-side variable $\frac{\text{Capital expenditure}_{i,t}}{\text{sale}_{i,t}}$ here represents our empirical proxy for firm's physical capital investment. In Panel (B), the left-hand-side variable $\frac{\text{R\&D expenses}_{i,t}}{\text{sale}_{i,t}}$ here represents our empirical proxy for firm's R&D expenditure. The rest variables are defined as in the same way as in Table 5. Data used in this table is at firm-year or firm-quarter level, and obtained from *Compustat*. Low-frequency nominal interest rate data is obtained from Fed St. Louis and high-frequency interest rate data is obtained from Nakamura and Steinsson (2018) and Acosta (2022). In all columns, we introduce firm- and year-fixed effects. T-statistics are in parentheses. *, **, and *** represent results significant at

Table A3: Double Sorting: Equal-Weighted Returns

Part I: Full Sample with Net Income ($\frac{\text{NI}}{GP}$) + Gross Profitability ($\frac{\text{GP}}{AT}$)

(A): Raw excess return (%)

		Gross Profitability						
		Low	2	3	4	High	Low-High	(t-stat)
	Low	6.18	12.02	13.69	16.28	17.67	11.49***	(4.75)
	2	8.13	9.58	12.64	13.92	16.29	8.16***	(4.38)
Net Earnings	3	9.15	8.56	9.83	11.96	14.20	5.04***	(2.45)
	4	13.49	7.82	8.63	9.98	11.89	-1.6	(0.5)
	High	6.65	7.84	8.43	9.58	10.42	3.77	(1.26)
	Low - High	-0.47	4.18	5.26**	6.70***	7.25***	11.02***	(4.78)
	(t-stat)	(-0.21)	(1.42)	(2.07)	(2.68)	(2.55)	(4.78)	

(B): α^{CAPM} **(%)**

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-3.65	2.26	4.68	7.35	9.53	13.18***	(5.71)
	2	-1.12	0.53	4.51	5.37	8.72	9.84***	(5.52)
Net Earnings	3	0.28	-0.14	1.62	4.11	6.20	5.92***	(3.10)
	4	1.85	-0.65	0.31	2.28	3.57	1.72	(0.58)
	High	-2.15	-0.50	0.30	1.70	2.18	4.34	(1.63)
	Low - High	-1.49	2.76	4.38**	5.65***	7.35***	11.68***	(5.30)
	(t-stat)	(-0.71)	(1.08)	(1.91)	(2.48)	(2.89)	(5.30)	

(C): α^{FF5} **(%)**

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-1.05	5.17	3.27	5.29	7.69	8.74***	(4.45)
	2	0.22	-1.16	2.07	4.40	5.98	5.76***	(3.92)
Net Earnings	3	-1.76	-1.94	0.60	3.51	3.96	5.72***	(4.40)
	4	4.74	-2.36	-0.26	1.56	4.28	-0.46	(-0.24)
	High	2.45	-1.12	-0.62	2.13	3.76	1.32	(0.69)
	Low - High	-3.5*	6.30***	3.88***	3.16*	3.93**	5.24***	(2.84)
	(t-stat)	(-1.93)	(3.66)	(2.64)	(1.85)	(2.18)	(2.84)	

(D): α^{HXZ} **(%)**

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-3.10	5.84	5.28	4.78	8.51	11.61***	(6.05)
	2	5.46	2.21	4.61	6.94	8.04	2.58*	(1.77)
Net Earnings	3	2.16	1.64	2.60	4.25	5.71	3.55***	(2.64)
	4	4.97	2.01	1.61	1.56	3.74	-1.23	(-0.60)
	High	4.85	1.86	2.02	2.44	4.15	0.70	(0.35)
	Low - High	-7.95***	3.99**	3.27**	2.35	4.36**	3.67**	(2.02)
	(t-stat)	(-4.27)	(2.23)	(2.13)	(1.41)	(2.42)	(2.02)	

Part II: Full Sample with Customer Capital Expenses ($\frac{\text{net XGSA}}{GP}$) + Gross Profitability ($\frac{GP}{AT}$)

(E): Raw excess return (%)

		Gross Profitability						
		Low	2	3	4	High	Low-High	(t-stat)
Customer Capital Expenses	Low	3.54	9.75	11.21	12.77	14.06	***	()
	2	7.85	9.15	10.32	11.74	14.56	10.52***	(3.90)
	3	9.33	11.38	11.04	12.62	15.53	6.71***	(3.47)
	4	9.11	11.47	14.52	15.37	14.98	6.20***	(3.15)
	High	4.43	13.17	16.31	14.27	16.75	5.87***	(2.20)
	High - Low	0.89	3.43	5.10*	1.50	2.69	12.32***	(4.17)
	(t-stat)	(0.31)	(1.15)	(1.80)	(0.58)	(0.92)	(4.17)	

(F): α^{CAPM} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
Customer Capital Expenses	Low	-5.13	0.83	1.94	3.86	5.18	10.31***	(4.23)
	2	-0.77	0.62	2.06	3.41	6.15	6.92***	(4.00)
	3	0.27	2.79	2.70	4.67	7.58	7.32***	(4.09)
	4	-0.81	3.93	6.68	7.28	6.77	7.58***	(3.12)
	High	-5.87	4.26	6.76	5.98	9.36	15.24***	(5.48)
	High - Low	-0.75	3.43	4.82*	2.12	4.19	14.49***	(5.64)
	(t-stat)	(-0.27)	(1.25)	(1.86)	(0.88)	(1.57)	(5.64)	

(G): α^{FF5} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
Customer Capital Expenses	Low	-0.15	0.55	3.65	7.77	7.42	7.56***	(4.09)
	2	-0.27	1.22	4.31	6.30	5.41	5.69***	(4.45)
	3	1.81	2.42	0.85	4.57	6.24	4.42***	(3.16)
	4	2.30	2.08	6.13	6.74	5.66	3.36*	(1.94)
	High	-0.35	6.19	4.88	1.46	5.04	5.39***	(2.34)
	High - Low	-0.21	5.63***	1.24	-6.31***	-2.38	5.18***	(2.62)
	(t-stat)	(0.09)	(2.90)	(0.58)	(-3.32)	(-1.15)	(2.62)	

(H): α^{HXZ} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
Customer Capital Expenses	Low	3.48	0.98	1.80	4.07	5.07	1.59	(0.82)
	2	2.38	1.99	2.37	4.73	3.72	1.34	(1.03)
	3	4.58	4.66	2.56	5.51	6.35	1.77	(1.19)
	4	2.88	2.74	6.17	9.86	7.11	4.23**	(2.24)
	High	-6.87	8.38	8.54	5.09	8.15	15.02***	(6.43)
	High - Low	-10.35***	7.40***	6.74***	1.02	3.08	4.67**	(2.16)
	(t-stat)	(-4.45)	(3.58)	(3.50)	(0.56)	(1.44)	(2.16)	

Part III: Subsample Excluding Micro Cap Stocks with Net Income ($\frac{\mathbf{NI}}{GP}$) + Gross Profitability ($\frac{\mathbf{GP}}{AT}$)

(I): Raw excess return (%)									
		Gross Profitability							
		Low	2	3	4	High	High-Low	(t-stat)
	Low	3.37	8.76	11.06	12.77	14.91	11.54***	(5.05)
	2	5.30	7.58	10.08	12.47	14.10	8.80***	(4.70)
Net Earnings	3	6.65	7.40	8.84	10.28	12.21	5.57***	(3.56)
	4	9.99	7.84	8.28	9.12	10.56	0.57	(0.18)
	High	5.76	7.57	7.47	8.53	9.23	3.46	(1.21)
	Low - High	-2.40	1.19	3.59	4.23**	5.68***	9.14***	(4.34)
	(t-stat)	(-1.16)	(0.43)	(1.59)	(1.97)	(2.30)	(4.34)	
(J): α^{CAPM} **(%)**								
		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-7.01	-0.43	1.92	3.97	6.19	13.21***	(6.05)
	2	-4.41	-1.64	1.51	3.65	5.80	10.21***	(5.96)
Net Earnings	3	-2.57	-1.49	0.63	2.36	3.90	6.47***	(4.47)
	4	-0.74	-0.94	-0.25	1.28	2.69	3.43	(1.15)
	High	-4.21	-0.95	-0.57	0.53	0.98	5.19***	(2.02)
	Low - High	-2.81	0.52	2.49	3.44*	5.21**	10.40***	(5.12)
	(t-stat)	(-1.41)	(0.23)	(1.24)	(1.76)	(2.39)	(5.12)	
(K): α^{FF5} (%)								
		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-3.22	2.11	-0.33	2.18	4.02	7.24***	(4.05)
	2	-1.81	-2.71	-0.45	3.81	3.58	5.39***	(3.97)
Net Earnings	3	-3.65	-2.84	0.75	1.23	2.92	6.57***	(5.76)
	4	1.40	-2.27	-0.68	1.59	3.47	2.07	(1.14)
	High	0.93	-1.80	-1.79	1.33	2.92	1.99	(1.11)
	Low - High	-4.15	3.91***	1.46	0.85	1.11	3.09*	(1.79)
	(t-stat)	(-2.48)	(2.58)	(1.09)	(0.60)	(0.68)	(1.79)	
(L): α^{HXZ} (%)								
		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-2.59	4.36	2.71	4.55	6.53	9.12***	(4.98)
	2	3.41	0.52	1.72	5.47	5.42	2.01	(1.56)
Net Earnings	3	1.19	0.49	2.44	3.31	4.78	3.59***	(3.08)
	4	3.32	1.70	0.97	1.24	3.34	0.02	(0.01)
	High	2.81	0.97	0.74	1.39	2.97	0.16	(0.09)
	Low - High	-5.40***	3.39**	1.97	3.16**	3.55**	3.72**	(2.14)
	(t-stat)	(-3.03)	(2.16)	(1.53)	(2.23)	(2.30)	(2.14)	

Part IV: Subsample Excluding Micro Cap Stocks with Customer Capital Expenses ($\frac{\textbf{net XGSA}}{GP}$) + Gross Profitability ($\frac{\textbf{GP}}{AT}$)

(M): Raw excess return (%)

		Gross Profitability						
		Low	2	3	4	High	Low-High	(t-stat)
	Low	3.60	9.73	10.28	11.61	12.14	8.54***	(3.38)
	2	7.22	8.88	10.65	10.94	13.43	6.21***	(3.20)
Customer Capital Expenses	3	7.65	9.59	9.59	11.83	13.00	5.35***	(2.80)
	4	8.36	9.71	11.16	13.27	13.50	5.15*	(1.96)
	High	0.76	9.86	11.86	11.68	14.28	13.52***	(4.50)
	High - Low	-2.84	0.13	1.58	0.08	2.14	10.68***	(4.57)
	(t-stat)	(-0.97)	(0.05)	(0.69)	(0.03)	(0.90)	(4.57)	

(N): α^{CAPM} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-4.89	0.62	0.94	2.71	3.10	7.98***	(3.51)
	2	-2.08	0.12	1.96	2.95	4.55	6.63***	(3.81)
Customer Capital Expenses	3	-1.06	0.57	1.48	3.65	4.81	5.87***	(3.39)
	4	-1.62	1.36	2.75	5.20	5.14	6.76***	(2.93)
	High	-9.36	1.52	2.51	3.19	5.76	15.12***	(5.31)
	High - Low	-4.47	0.89	1.57	0.48	2.67	10.65***	(4.83)
	(t-stat)	(-1.57)	(0.38)	(0.74)	(0.23)	(1.28)	(4.83)	

(O): α^{FF5} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	-0.80	0.90	3.35	8.29	6.02	6.82***	(4.05)
	2	-0.95	1.42	3.23	5.30	5.90	6.84***	(5.13)
Customer Capital Expenses	3	0.35	0.51	1.66	4.32	3.78	3.43***	(2.60)
	4	1.84	0.61	2.35	5.36	3.84	2.00	(1.25)
	High	-3.17	1.86	-0.54	0.31	5.14	8.31***	(3.71)
	High - Low	-2.37	0.96	-3.89***	-7.98***	-0.88	5.94***	(3.49)
	(t-stat)	(-1.05)	(0.56)	(2.34)	(-4.59)	(-0.53)	(3.49)	

(P): α^{HXZ} (%)

		Gross Profitability						
		Low	2	3	4	High	High-Low	(t-stat)
	Low	3.49	1.58	1.74	2.89	4.18	0.69	(0.38)
	2	0.45	1.04	1.43	4.61	4.81	4.35***	(3.27)
Customer Capital Expenses	3	3.18	2.62	3.06	3.89	4.28	1.10	(0.77)
	4	3.57	2.93	2.02	6.52	5.61	2.04	(1.03)
	High	-6.32	4.12	3.72	5.27	7.93	14.25***	(6.14)
	High - Low	-9.81***	2.54	1.98	2.38	3.75***	4.44***	(2.45)
	(t-stat)	(-4.23)	(1.43)	(1.24)	(1.54)	(2.34)	(2.45)	

Notes: This table reports the average equal-weighted excess stock returns of 25 portfolios two-way sorted on net earnings ($\frac{\text{NI}}{GP}$)/customer capital expenses ($\frac{\text{net XGSA}}{GP}$) and gross profitability ($\frac{\text{GP}}{AT}$). Definitions of these variables are as in Section 2.1. The raw excess return is the average annualized portfolio excess stock return. α^{CAPM}, α^{FF5}, and α^{HXZ} are portfolio average abnormal returns, obtained as the intercept from monthly CAPM, Fama and French (2015) five-factor model, and Hou, Xue and Zhang (2008) q-factor model regressions, respectively. All of them are reported in annual percentages. *t*-stats are heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). Part I and II report the results for the full sample, meanwhile Part III and IV present the corresponding outcomes in a subsample excluding micro cap stocks. The micro cap firms are defined as firms with a market capitalization lower than the bottom 20th percentile of all NYSE firms. The sample period is from July 1970 to June 2019. Data is obtained from *CRSP* and *Compustat*.