The Change in Corporate Production Function: Theory and Evidence

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Abstract

The assumption of a concave production function is a key foundation in the economics literature. However, using the Bayesian Markov Chain Monte Carlo (MCMC) changepoint estimation, we document that the corporate production function has changed to a sigmoidal (convex-concave) one since the 1980s, and the convexity component has become increasingly important over time. This long-run trend occurs for the majority of the industries. Finally, we build a dynamic framework to study the implications of such change in production function on markup, net earnings, and asset prices, and provide empirical evidence.

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

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1 Introduction

At least since the work of Charles W. Cobb and Paul H. Douglas (1928), the assumption of a concave production function (e.g., Cobb-Douglas, Constant Elasticity of Substitution) has been a fundamental feature of macroeconomic models, with broad implications for economic growth, resource allocation, and business cycles. However, we document that the corporate production function has changed to a sigmoidal (convex-concave) one since the 1980s, and the convexity component has become increasingly important over time. We further demonstrate that this long-run trend occurs within the large majority of countries and industries. Finally, we show that the shift in the shape of production function has important implications for market power, net earnings, and asset prices.

We start by investigating the long-run evolution of corporate production function with a firm-level dataset on the accounts of all publicly traded companies in the U.S. We adopt the Bayesian Markov Chain Monte Carlo (MCMC) changepoint estimation as it is more flexible and imposes few restrictions on the production function structure. Our investigation uncovers a noteworthy shift since 1980, as the corporate production function transitions towards a convex-concave configuration, with the convexity factor progressively gaining prominence over the years. In our baseline analysis, the estimated convexity-concavity threshold capital level, at which point the production changes from convex to concave, is $10^{2.42}$ thousand dollars (or 0.25 in terms of quantile) in 1980. However, it has changed to $10^{7.79}$ thousand dollars (or 0.70 in terms of quantile) in 2021. Our main findings are robust to using alternative functional forms. Additionally, our analysis demonstrates that this enduring trend is pervasive across diverse industries and advanced economies, where the most pronounced pattern happens in the manufacturing and services-related sectors.

We then leverage this empirical evidence to explore the broader implications of the altered corporate production function on the macroeconomic landscape. Our attention is directed towards the surge in popularity of firms with negative net earnings, the origins of market power, and intriguingly distinct implications for asset pricing. To begin with, we find that 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. We also observe a similar upward trend based on the Initial Public Offerings (IPO) dataset. In 1980, only 24% of companies were not making money when they went public. However, this number increased to

77% in 2019. More importantly, we find a positive and significant relationship between the convexity-concavity threshold and the share of unprofitable firms: industries with higher thresholds are associated with a higher fraction of firms with negative net earnings. In other words, the changing economies of scale arising from new technologies such as digitization indeed transform the corporate business model and the nature of competition between firms.

After that, we test whether the shape of production function is one of the important origins of corporate market power. The first supporting evidence is that industries with higher convexity-concavity thresholds indeed have higher levels of markup. This positive relationship is both statistically and economically significant in the data. In addition, the impacts of changing production functions also show up at the firm-level investment on customer capital. We empirically document that firms with higher markups tend to have higher customer capital expenses and lower net earnings. Different from our conventional wisdom, nowadays, firms with more negative net earnings are associated with higher market power, as they have stronger incentives to spend substantial resources on customer capital. Our empirical evidence here complements William Ginsberg (1974)'s theoretical study, which shows that winners-take-all is an efficient resource allocation plan with convex-concave technology.

Finally, we explore the asset pricing implication of changing corporate production functions. We first use a standard investment model to show that the shape of the production function matters a lot for stock returns. The model generates a negative relationship between the net-earnings-to-gross-profit (NEGP) ratio and stock return under the traditional decreasing-return-to-scale (DRTS) production function, but a positive relation under the production function that is increasing-return-to-scale (IRCS) for capital level below the threshold, and DRTS above. We document the following four supporting empirical patterns in the data. First, longing low-NEGP (or high-ratios-of-customer-capital-expenses-to-gross-profitability, high-CCGP afterward) 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., Robert 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 the capital asset pricing model (CAPM), the Fama-French five-factor model (Eugene F. Fama and Kenneth R. French, 2015), and the q-factor model (Kewei Hou, Chen Xue and Lu 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 Eugene F. Fama and James D. 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 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 belongs to the growing literature on the changing characteristics of firms in the 21st century. Jan De Loecker, Jan Eeckhout and Gabriel Unger (2020) document a substantial increase in market power for the U.S. public firms since 1980. Gerard Hoberg and Gordon Phillips (2021) show that firms have also largely expanded their scope and scale of operations over the past 30 years. In addition, David Autor, David Dorn, Lawrence F. Katz, Christina Patterson and John Van Reenen (2020) show the growing importance of superstar firms that dominate the market. Callum Jones and Thomas Philippon (2016) and German Gutierrez and Thomas Philippon (2017) document the declining competition and investment among U.S. firms. Our work adds another important trend of modern companies to the existing literature.

Second, our paper connects to the convex-concave production function used in the economics literature. This structure is particularly relevant in development economics, where economies often undergo transitions from low levels of development characterized by increasing returns to higher levels marked by diminishing returns. Early theoretical contributions can date back to Zvi Griliches (1957), Ginsberg (1974), A. K. Skiba (1978), and many others. After that, many studies have used convex-concave production functions to explain the poverty traps phenomenon, where developing economies are stuck at low levels of income (e.g., Costas Azariadis and Allan Drazen, 1990; Philippe Askenazy and Cuong Le Van, 1999; Ken-Ichi Akao, Takashi Kamihigashi and Kazuo Nishimura, 2011). With a nonconcave aggregate production function, whether the economy's trajectory moves toward the high steady state or the low one, hinges on the initial capital per capita level. Most of these studies are theoretical and focused on country-level analysis. In contrast, our work provides the first piece of firm-level evidence and documents the increasing importance of the first convexity component over time.

Third, our paper is closely related to the growing literature on corporate behaviors and asset prices. For instance, Joao F. Gomes, Leonid Kogan and Motohiro Yogo (2009) document and explain the cross-sectional relationship between product durability and asset prices. Frederico Belo, Xiaoji Lin and Santiago Bazdresch (2014) study how labor hiring affects cross-sectional stock returns. Meanwhile, Ayşe İmrohoroğlu and Şelale Tüzel (2014) study how the firm-level total factor productivity (TFP) affects asset prices. M. Cecilia Bustamante and Andres 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. Alexandre Corhay, Howard Kung and Lukas 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, Winston Wei Dou, Shane A. Johnson and Wei 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 impacts of the shape of the production function on the cross-sectional return spread.

Fourth, our work belongs to the production function estimation literature. The previous studies are focused on estimating firm-level TFP by proposing various techniques to solve the possible simultaneity issue and selection bias (e.g., G Steven Olley and Ariel Pakes, 1996; James Levinsohn and Amil Petrin, 2003; Jeffrey M Wooldridge, 2009; Daniel A Ackerberg, Kevin Caves and Garth Frazer, 2015). Compared to the previous literature, our Bayesian MCMC approach is more flexible and thus able to capture the time-series evolution of production function. In addition, our firm-level investigation is a supplement to the previous country-level estimation on aggregate production function (e.g., Robert Solow, 1957; Paul Samuelson, 1979; Robert E. Hall and Charles I. Jones, 1999).

Layout The rest of the paper is organized as follows. Section 2 presents the empirical framework and data sources that allow us to flexibly estimate the time-varying changes in the corporate production function. Section 3 summarizes our key findings on the changing production function for public firms.In Section 4, we further explore its implications on market power, net earnings, and asset pricing. Finally, Section 5 concludes.

2 Empirical Methodology and Data

2.1 Methodology

Our goal is to impose very few restrictions on the structure of the sequence of the inflection points so that our methodology can better reveal the underlying evolution in the data. Specifically, we assume that in each cross-section (i.e., each year), each firm represents the current-period economic mechanism. When the total capital of firm i does not reach the thresholding turning point, firm i experiences an increasing return to scale. Afterward, once the capital accumulation exceeds the inflection point, the firm switches to a decreasing return to scale. The econometric problem is that we cannot observe both returns to scale of the same firm simultaneously. We hence assume that the firms in the cross-section are random realizations along the production function. In cross-section t ranging from 1980 to 2021, we implement Bayesian changepoint estimation (CPE) to estimate the inflection point ($\bar{k}_t$). The time series of $\bar{k}_t$ demonstrate the evolution of the inflection points and thus capture the underlying changes in corporate production function.

2.2 Changepoint Estimation

Changepoint estimation is widely adopted in detecting abrupt changes in time series, revealing systematic changes in the underlying data-generating mechanism. In a general sense, changepoint estimation methods can be classified according to whether the observation from the system is made online (e.g., Ryan Prescott Adams and David JC MacKay, 2007) or offline. From a statistical viewpoint, changepoint estimation can also be categorized into frequentist and Bayesian (e.g., Bradley P Carlin, Alan E Gelfand and Adrian FM Smith, 1992; David A Stephens, 1994). The number of changepoints can be either known beforehand or estimated from data. A more detailed description of the changepoint methods can be found in Charles Truong, Laurent Oudre and Nicolas Vayatis (2020) which reviews a large body of existing changepoint estimation methods.

In economic analysis, changepoint often represents structural breaks in the economy (e.g., Jushan Bai, 1997; Jushan Bai, Robin L Lumsdaine and James H Stock, 1998; Brian M Doyle and Jon Faust, 2005;

Zhongjun Qu and Pierre Perron, 2007). Pierre Perron et al. (2006) provides a comprehensive review of techniques to deal with structural breaks. In our application, we assume the existence of a single unknown changepoint according to a model of the production function and consider an offline Bayesian changepoint estimation. Our model is mostly closely related to Carlin, Gelfand and Smith (1992) and Stephens (1994), and we estimate the changepoint using Bayesian MCMC.

Two challenges of the model promote our adoption of Bayesian MCMC. First, our model is on the relationship between output and capital, a continuous variable, hence not a time-series setting. Therefore, the likelihood-based maximizing-searching technique can be cumbersome because it is impossible to search a continuous interval. Second, besides the changepoint, we are also interested in the return-to-scale parameters. For each of the marginal distributions of the parameters, it is difficult to integrate other parameters. Bayesian MCMC samples from the posterior joint distribution of the parameters by generating a Markov Chain based on the univariate conditional posterior distributions. Therefore, Bayesian MCMC does not need to search the interval or integrate over auxiliary parameters. The computational efficiency of Bayesian MCMC is also well documented in the literature (e.g., Stephens, 1994).

2.2.1 The Baseline Functional Form

Assuming a single change in a time series, a changepoint is when the data starts to exhibit inconsistency with previous observations. Such inconsistency can be a level difference (mean), a trending difference (slope), a variability difference (variance), or a combination of these. Assume that a firm i's total output is y and its total capital stock, including both physical and intangible capital, is denoted as k. The structural change is assumed to occur at $\bar{k}_t$. In this way, our production function to be estimated can be written as follows:

$$y_{it} = \begin{cases} A_{1t} Z_{1it} k_{it}^{\alpha_t^a} & \text{if } k_{it} < \bar{k}_t \\ A_{2t} Z_{2it} k_{it}^{\alpha_t^e} & \text{if } k_{it} \geq \bar{k}_t, \end{cases} \tag{1}$$

where Z_{1it} and Z_{2it} are independent log-normal distributed. It is worth noting that when estimating the model, we do not impose the condition that $\alpha^a > 1$ and $\alpha^e < 1$. The data will inform us of the value of these two parameters. Taking logarithms on both sides and reparameterizing yield

$$\log y_{it} = \begin{cases} a_{1t} + \alpha_t^a \log k_{it} + \varepsilon_{1it} & \text{if } k_{it} < \bar{k}_t \\ a_{2t} + \alpha_t^e \log k_{it} + \varepsilon_{2it} & \text{if } k_{it} \geq \bar{k}_t, \end{cases} \tag{2}$$

where $\varepsilon_{1it} \sim \mathcal{N}(0, \sigma_1^2)$ is independent of $\varepsilon_{2it} \sim \mathcal{N}(0, \sigma_2^2)$. Model (2) is cross-sectional, and the parameters are specific to the cross-section. Changepoint can still apply to this model, treating capital as a continuous "timing" variable.

2.2.2 Bayesian MCMC

Bayesian MCMC is a simulation-based sampling estimation strategy that receives more and more attention in economic and financial studies. MCMC offers a convenient way to estimate continuous changepoints, which is much more complicated than discrete ones. For a complicated joint posterior distribution with too many dimensions, the MCMC sampler simulates each univariate conditional posterior iteratively. Under mild conditions, such conditionally sampled densities aggregate to approximate the joint desired posterior distribution. For a more detailed description of the Bayesian MCMC, please refer to Erica X.N. Li, Haitao Li, Shujing Wang and Cindy Yu (2019) and Erica X.N. Li, Guoliang Ma, Shujing Wang and Cindy Yu (2021).

In particular, denote the observed data as $\boldsymbol{Y}_t = \{Y_{it}, i = 1, \ldots, N_t\}$ and $\boldsymbol{k}_t = \{k_{it}, i = 1, \ldots, N_t\}$. The joint likelihood $f(\boldsymbol{Y}_t, \boldsymbol{k}_t \mid \boldsymbol{\theta}_t)$ is proportional to

$$\frac{1}{\sqrt{2\pi\sigma_1^2}^{n_1}\sqrt{2\pi\sigma_2^2}^{n_2}} \exp\left\{-\frac{\sum_{i:k_{it}<\bar{k}_t}[\log y_{it} - (a_{1t} + \alpha_t^a \log k_{it})]^2}{2\sigma_1^2} - \frac{\sum_{i:k_{it}\geq\bar{k}_t}[\log y_{it} - (a_{2t} + \alpha_t^e \log k_{it})]^2}{2\sigma_2^2}\right\}, \tag{3}$$

where n_1 and n_2 are the number of observations with $k_{it} < \bar{k}_t$ and $k_{it} \geq \bar{k}_t$ for a given $\bar{k}_t$.

Bayesian statistics differ from frequentist statistics in viewing parameters as random variables. The prior distributions of parameters reflect the subjective belief of the researchers about the parameters. Denote the priors on parameters as $\pi(\boldsymbol{\theta})$. The posterior is then proportional to $f(\boldsymbol{Y}_t, \boldsymbol{k}_t \mid \boldsymbol{\theta}_t)\pi(\boldsymbol{\theta})$. In terms of inference, since MCMC draws from the posterior distributions, interval estimations are readily available. For a point estimate $\hat{\theta}$, we approximate its *credible interval* with $[\hat{\theta} - 2\hat{s}, \hat{\theta} + 2\hat{s}]$, where $\hat{s}$ is the estimated posterior standard deviation. As for changepoint applications with MCMC, please refer to Carlin, Gelfand and Smith (1992) and Stephens (1994) for computational details. In our estimation, we tune the proposal density with at most 2,000 iterations and simulate 20,000 Monte Carlo samples with a Metropolis-Hasting embedded Gibbs sampler.

2.3 Data

Data used for our empirical analysis 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", excluding financial firms (SIC 6000-6999) and regulated utilities (SIC 4900-4999), and drop firms with missing/negative values on assets or sales. 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.

All variables are constructed by following some recent studies or the standard practice in the empirical corporate finance literature. 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*). Given the increasing importance of intangible capital, we use the intangible capital measure constructed by Ryan H. Peters and Lucian A. Taylor (2017) and compute the total capital stock as the sum of tangible capital (*Compustat* data item *PPENT*) and intangible capital. 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 on 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. 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 the cost of goods sold (*Compustat* data item *COGS*) from total revenue (*Compustat* data item *REVT*). Following the work of Monica Morlacco and

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

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 (Randolph B. Cohen, Paul A. Gompers and Tuomo Vuolteenaho, 2002). Finally, we exclude financial firms (SIC 4900-4999) and regulated firms (SIC 6000-6999) in our sample.

3 Trends in Corporate Production Function

3.1 Baseline Evidence

We present the estimated turning points from convexity to concavity in Graph (a) of Figure 1. This baseline result is based on a cross-sectional analysis of all firms from all industries except finance services and utility. According to this figure, we can observe a clear upward trend in the estimated threshold over time, which indicates that for companies, the first increasing-returns-to-scale part has become substantially more and more important over the years. The estimated breaking point is $10^{2.42}$ thousand dollars in 1980. However, it has changed to $10^{7.79}$ thousand dollars in 2021. In other words, compared to their counterparts forty years ago, modern companies have a relatively more important convex portion with increasing returns-to-scale. Given the fact that production functions are a fundamental concept in economics that relate inputs to outputs in the production process, this long-run shift in the shape of production function is an important trend for economics literature, as the standard concave production function (e.g., Cobb-Douglas, Constant Elasticity of Substitution) remains the prevailing format in both theoretical and empirical investigations.

[Figure 1 here]

To mitigate the concern that this upward trend in threshold might purely come from the increasing firm size, we also report the quantile of the estimated changepoint in each year. More specifically, for each year t, we compute the relative rank of this convexity-concavity threshold as $r_t = \hat{F}_k(\hat{\bar{k}}_t)$, where $\hat{F}_k$ is the empirical cumulative distribution function of total capital. The corresponding result is presented in Graph (b) of Figure 1. Similarly, there is also an upward trend in the quantile of the estimated threshold, which again indicates the increasing importance of production convexity over time. In terms of the magnitudes, the estimated breaking point in terms of quantile is 0.25 in 1980. However, this number has increased to 0.70 in 2021. It means that for all the U.S. public firms in 2021, 70% of them are still in the increasing return-to-scale stage.

Finally, we present the time-series plots of estimated degrees of returns-to-scale in Graph (c) of Figure 1. It is worth noting that we do not impose any restrictions on the magnitudes of these slopes when estimating the model. The data suggests that there are indeed two distinct components in the aggregate production function, where the first component shows increasing returns-to-scale with an estimated slope coefficient α^a larger than 1, and the second one has a feature of decreasing returns-to-scale with an estimated coefficient α^e smaller than 1. Although there are some fluctuations in the measured degrees of returns-to-scale over time, throughout our sample, the average values of estimated coefficients α^a and α^e are 1.19 and 0.98, respectively.

public v.s. full-sample Due to the data limitation, we conducted our empirical analysis in a dataset with public firms only. However, it does not affect our key conclusion as our main focus is on finding the long-run changes in the convexity-concavity thresholds. As private firms are usually smaller and have not reached their concavity production period, using a dataset with both private and public companies will not significantly affect our main conclusion drawn from Graph (a). However, it does affect the estimated slope coefficients in Graph (c), especially for the first convexity component. In this perspective, the recent literature on the IPO listing gap (e.g. Craig Doidge, G. Andrew Karolyi and Rene M. Stulz, 2017) can help us understand why there is a decreasing trend in the estimated degree of convexity over time. In other words, we could potentially underestimate the degree of convexity with a dataset containing public firms only.

3.2 Robustness Checks

In this section, we provide a battery of additional tests to show the robustness of our main conclusions in the baseline analysis.

3.2.1 Simulation

To begin with, we verify the efficacy of Bayesian MCMC changepoint estimation with simulation studies. We conduct this simulation exercise to show the ability of our methodology to correctly detect the time-series changes in thresholds. In this example, in each cross-section, we set the 30% quantile of the total capital as the changepoint and set $\alpha_a = 1.3$ and $\alpha_e = 0.7$. We also assign the pre-mature firms with higher variability in output. More specifically, our true model specification in this simulation exercise is shown as follows:

$$\log y_{it} = \begin{cases} -3 + 1.3 \log k_{it} + \varepsilon_{1it} & \text{if } k_{it} < \bar{k}_t \\ -0.5 + 0.7 \log k_{it} + \varepsilon_{2it} & \text{if } k_{it} \geq \bar{k}_t, \end{cases} \tag{4}$$

where the error terms ε_{1it} and ε_{2it} are independently distributed according to $\varepsilon_{1it} \sim \mathcal{N}(0, 0.49)$ and $\varepsilon_{2it} \sim \mathcal{N}(0, 0.25)$. We set the coefficients and the relative quantiles to be the same values as the total capital changes in each year. More importantly, as we estimate the changepoints independently in each cross-section, this setup is closer to what happens in reality.

[Figure 2 here]

With the simulated dataset, we can redo our previous analysis with the Bayesian MCMC changepoint estimation approach. The corresponding estimated results of the convexity-concavity threshold and slope coefficients are presented in Graphs (a) and (b) in Figure 2. According to these two graphs, our methodology is able to correctly detect the turning point when there is one in the underlying data. More importantly, the estimated thresholds with our Bayesian MCMC approach are indeed the true values. In addition, the estimated slope coefficients are also close to the actual ones. Therefore, our simulation studies verify the efficiency of our Bayesian methodology.

3.2.2 Alternative Functional Form

After that, we test whether our main findings still hold if we choose alternative functional forms of this convex-concave production.

continuity To begin with, our baseline model (i.e., Equation (2)) does not assume the production function's continuity, hence making the aggregate production function discontinuous at the turning point $\bar{k}_t$. As a robustness check, we impose continuity at $\bar{k}_t$ such that $a_{1t} + \alpha_t^a \log \bar{k}_t = a_{2t} + \alpha_t^e \log \bar{k}$. Solving for a_{2t} and incorporating the restriction into model (2), we can rewrite the previous equation as below:

$$\log y_{it} = \begin{cases} a_{1t} + \alpha_t^a \log k_{it} + \varepsilon_{1it} & \text{if } k_{it} < \bar{k}_t \\ a_{1t} + (\alpha_t^a - \alpha_t^e) \log \bar{k}_t + \alpha_t^e \log k_{it} + \varepsilon_{2it} & \text{if } k_{it} \geq \bar{k}_t. \end{cases} \tag{5}$$

Again we redo our baseline analysis but this time with a continuous convex-concave production function. The estimated results of changepoints and slope coefficients under the continuity restriction are presented in Graph (c) and (d) in Figure 2. According to these two graphs, our main conclusion does not change with this modified model specification. Similarly, we can observe the upward trend in the estimated convexity-concavity threshold and thus the increasing importance of production convexity over time. However, the precise magnitudes are slightly different from our baseline analysis. The estimated breaking point is $10^{3.87}$ thousand dollars in 1980, and it has changed to $10^{7.79}$ thousand dollars in 2021. In addition, throughout our sample, the average values of estimated slope coefficients are 1.20 and 0.98, respectively.

exponential functional form Another functional form widely used in the convex-concave production function literature is the following S-shaped one:

$$y_{it} = \frac{A_t Z_{it}}{1 + e^{-\gamma_t(\log k_{it} - \bar{k}_t)}}, \tag{6}$$

where we assume that $\log Z_{it}$ follows an iid normal distribution $\mathcal{N}(0, \sigma^2)$. The definitions of y and k are the same as in our baseline model (Equation (2)). Taking log on both sides and redefining $a_{it} \equiv A_t$ and $\varepsilon_{it} \equiv Z_{it}$, we have

$$\log y_{it} = a_t - \log(1 + \exp\{\gamma_t \bar{k}_t - \gamma_t \log k_{it}\}) + \varepsilon_{it}. \tag{7}$$

Compared to the functional form used in our baseline estimation, this S-shaped exponential form is smooth and continuously differentiable at each point, thus generating more advantages for the theoretical studies. For this model, we estimate the parameters by maximum likelihood method because of its simple form. The standard error and t-values of the estimators are based on the inverted observed Fisher information. The estimated results of the convexity-concavity threshold and slope coefficient (γ) are presented in Graphs (e) and (f) in Figure 2, respectively. According to these graphs, we can still observe an upward trend in the estimated convexity-concavity threshold. With this S-shaped functional form, the estimated breaking point is $10^{4.73}$ thousand dollars in 1980, and it has changed to $10^{7.20}$ thousand dollars in 2021. This pattern is consistent with what we have found in the baseline analysis. In addition, the average value of coefficient γ is estimated to be 1.16 in our sample. Therefore, our main conclusions are robust to using alternative functional forms.

3.2.3 Industry-level Evidence

We complement our analysis with industry-level data. We estimate the changepoints for each of the Fama-French ten industry classifications. The definition of Fama-French ten industries is listed as follows: *Consumer Nondurables* (SIC 0100-0999, 2000-2399, 2700-2749, 2770-2799, 3100-3199, 3940-3989); *Consumer Durables* (SIC 2500-2519, 2590-2599, 3630-3659, 3710-3711, 3714-3714, 3716-3716, 3750-3751, 3792-3792, 3900-3939, 3990-3999); *Manufacturing* (SIC 2520-2589, 2600-2699, 2750-2769, 2800-2829, 2840-2899, 3000-3099, 3200-3569, 3580-3621, 3623-3629, 3700-3709, 3712-3713, 3715-3715, 3717-3749, 3752-3791, 3793-3799, 3860-3899); *Oil, Gas, and Coal Extraction and Products* (SIC 1200-1399, 2900-2999); *Business Equipment*

(SIC 3570-3579, 3622-3622, 3660-3692, 3694-3699, 3810-3839, 7370-7372, 7373-7373, 7374-7374, 7375-7375, 7376-7376, 7377-7377, 7378-7378, 7379-7379, 7391-7391, 8730-8734); *Telephone and Television Transmission* (SIC 4800-4899); *Wholesale, Retail, and Some Services* (SIC 5000-5999, 7200-7299, 7600-7699); *Healthcare, Medical Equipment, and Drugs* (SIC 2830-2839, 3693-3693, 3840-3859, 8000-8099); *Utilities* (SIC 4900-4949); and *Others*. Figure 3 shows the estimated trends of each of the ten industries. In addition, Table 1 summarizes the average values of these estimates throughout our sample. Credible intervals on the parameters and functions of the parameters are also from the posterior distributions obtained with Bayesian MCMC.

[Figure 3 here]

According to this figure, we can observe a long-run upward trend in the estimated threshold in all these ten industries. However, it does not necessarily mean that this changing shape of production function happens in all industries. We still need to verify whether the estimated degrees of returns-to-scale are significantly different between the first and second components. According to the reported results in Table 1, we do observe a long-run shift in the shape of corporate production in 6 out of the 10 industries, and they are *Consumer Nondurables*, *Manufacturing*, *Business Equipment*, *Wholesale, Retail, and Some Services*, *Healthcare, Medical Equipment, and Drugs*, and *Others*. In addition, the most pronounced trend happens in the manufacturing and services-related sectors. In contrast, this shift is less apparent in industries like *Telephone and Television Transmission* and *Utilities*. We argue that this long-run trend is still of great importance to the whole economy as the manufacturing and services industries are the main engines of economic growth.

[Table 1 here]

4 Implications

4.1 Corporate Earnings

4.1.1 Hypothesis

Compared to an economy with the standard concave production function, the trajectory of a single firm's profits is quite different with the sigmoid technology. Therefore, in this section, we discuss its implications on corporate net earnings, as well as provide the supporting evidence in the following section. In the standard model with only decreasing returns-to-scale, a young and capital-poor firm has the highest marginal productivity of capital at the beginning of its life cycle. However, in an economy with an S-shaped production function, a young firm's marginal product of capital and profits are lowest in the first convexity component. Therefore, in this new economy, firms could easily make negative profits at the beginning. The short-run increasing returns-to-scale eventually allows the firm to become profitable.

The theoretical framework in our mind is mainly based on Francois Gourio and Leena 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 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.[1]

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 impact 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).

4.1.2 Evidence

Figure 4 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 is unweighted. As we can see from Figure

[1]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 continued to report high operating expenses and large losses.

4, 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 was 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 4 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.[2]

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 the 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

[2]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.

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 fluctuates around some value over time. There is no clear upward trend associated with this indicator.

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 the 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.

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 4, 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., James 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, to obtain market power in the future. Following this interpretation, we should not include those expenses when measuring the current markup.

evidence from IPO Now we supplement our previous analysis with the IPO dataset provided by Jay Ritter. Figure 5 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 earnings losses to the total number of firms going public in that year. The solid blue line in Figure 5 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 5 here]

More importantly, this upward trend is not entirely driven by the increasing IPOs for IT firms. The gray dotted line in Figure 5 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, this is no longer the case. Although the share of IPOs with negative income has increased substantially during this period, the fraction of IT stocks remains 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.

4.1.3 Convexity-Concavity Threshold and Unprofitable firms

Last but not least, we test whether the fraction of unprofitable firms is higher in industries with higher convexity-concavity turning points. We use the Fama-French 10 industry classifications here to correctly estimate the production function with sufficiently large observations.

Figure 6 presents the binscatter plot between our industry-level measure of convexity-concavity threshold and the share of firms with negative net earnings. The gray dashed line represents the linear-fit regression. This figure clearly shows a positive and significant relationship between these two variables: industries with higher thresholds indeed have a higher fraction of firms with negative net earnings. This significant and positive association in the data supports our technical change hypothesis. Companies in industries with relatively higher thresholds 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 6 here]

We also report the regression results with different controls and fixed effects in Table 2. Based on this table, we can see that this positive and significant association remains robust across various model specifications. In terms of economic significance, our result shows that one standard deviation (2.47) increase in the convexity-concavity threshold is associated with a 1.73-4.69 percentage points increase in the share of unprofitable firms. The latter is equivalent to an increase of 0.10-0.27 standard deviations. Our empirical finding implies that the close relationship between the shape of production function 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 2 here]

4.2 Market Power

In this section, we test whether the shape of production function is one of the important origins of corporate market power. Ginsberg (1974) analyzed how resources are allocated among different plants characterized by production technologies described by convex-concave functions. The key implication is that under some parameter restrictions with this sigmoid technology, the optimal resource allocation plan is that the most efficient plant takes over all the production, meanwhile the rest is inactive. Therefore, if we indeed find that the changing production function is one important reason why we observe the rise of corporate markup in the data, then these natural monopolies could be an efficient outcome.

4.2.1 Industry-level Evidence

We start by investigating the relationship between convexity-concavity threshold and markup at the industry level. Similar to what has been done in Section 4.1.3, here we empirically test whether the degree of markup is higher in industries with higher returns-to-scale. Figure 7 presents the binscatter plot between our industry-level measure of convexity-concavity threshold and markup. The gray dashed line represents the linear-fit regression. Similarly, Figure 7 presents a positive and significant relationship between these two variables: industries with higher importance of convexity component indeed have higher levels of markup. Similarly, we also report the regression results with different controls and fixed effects in Table 3. Based on this table, we can see that this positive and significant association remains robust across various model specifications. In terms of economic significance, our result shows that one standard deviation (2.47) decrease in the convexity-concavity threshold is associated with a 4.94-21.49 percentage points increase in markup. The latter is equivalent to an increase of 0.12-0.52 standard deviations. Our empirical finding implies that this positive relationship is also economically significant. Our empirical finding supports the view that the shape of production function could be an important source of corporate market power. In addition, the increasing importance of the convexity component could be one of the reasons why we observe the rise of markup in the data (De Loecker, Eeckhout and Unger, 2020).

[Figure 7 here]

[Table 3 here]

Our work here 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 Matthias Kehrig and Nicolas 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. In terms of the second category of the literature, Jan De Loecker, Jan Eeckhout and Simon Mongey (2021) demonstrate that technological innovation and market structure changes contribute to the rise in market power. Most of the existing studies are focused on changes in corporate internal financing (e.g., Thomas W. Bates, Kathleen M. Kahle and Rene M. Stulz, 2009), investment (e.g., Gutierrez and Philippon, 2017), or profitability (e.g., Carter Davis, Alexandre Sollaci and James Traina, 2021). Compared to the existing literature, this paper focuses on the production function origin in a winner-take-all economy.

4.2.2 Firm-level evidence

Here we argue that the impacts of changing production function could show up at the firm-level investment on customer capital. A growing number of studies have documented a substantial increase in average markups in both the U.S. and many other advanced economies (e.g., Christopher J. Nekarda and Valerie A. Ramey, 2013; De Loecker, Eeckhout and Unger, 2020; Gauti B. Eggertsson, Jacob A. Robbins and Ella Getz Wold, 2018; Sara Calligaris, Chiara Criscuolo and Luca 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 Ernest Liu, Atif Mian and Amir Sufi (2019) highlight the role of low interest rates in contributing to the rise of market power. Besides, Nicolas Crouzet and Janice C. Eberly (2018) and James E. Bessen (2016) focus on the intangible-capital or IT-capital origin of corporate market power, respectively. Finally, Hendrik Dopper, Alexander MacKay, Nathan H. Miller and Joel Stiebale (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 between customer capital and market power can be best illustrated in Figure 8. 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 8 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 8 here]

Similarly, we can obtain the time-varying correlation between a firm's markup and its net earnings. The blue line in Figure 8 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 (Maarten 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 if 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 4. The general model specification used in Table 4 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 on 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 4 here]

Columns (1) - (9) in Panel A of Table 4 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 4, 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 4 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.

4.3 Asset Pricing Implications

4.3.1 Model and predictions

In this section, we show that the standard investment model generates a negative NEGP-return relation under the traditional DRTS production function, but a positive relation under the IRCS production function.

We adopt the estimated investment model in Hang Bai, Erica X.N. Li, Chen Xue and Lu Zhang (2023), which is a simplified setup of Lu Zhang (2005) and Hang Bai, Kewei Hou, Howard Kung, Erica X.N. Li and Lu Zhang (2019). The production function is

$$\Pi_{it} = \Pi(K_{it}, Z_{it}, X_t) = X_t Z_{it} K_{it}^{\alpha_{it}} - f \tag{8}$$

in which Π_{it} is firm i's operating profits, K_{it} is capital, X_t is aggregate productivity, Z_{it} is firm-specific productivity, and $f > 0$ is the fixed cost of production. The key element of the model is the production curvature parameter:

$$\alpha_{it} = \alpha^H \times \mathbb{I}_{K_{it} < \bar{K}} + \alpha^L \times \mathbb{I}_{K_{it} \leq \bar{K}} \tag{9}$$

in which $\mathbb{I}_{\{\cdot\}}$ is the indicator function that equals one if the event in $\{\cdot\}$ is true and zero otherwise, and $\alpha^H > 1 > \alpha^L > 0$ are constant parameters. $\bar{K}$ is the threshold capital, below which production technology exhibits ITCS and, above which, DRTS. In our baseline model, we set $\bar{K} = 0$, under which the model is identical to the one in Bai et al. (2023).

The aggregate productivity, X_t, has a stationary Markov transition function:

$$x_{t+1} = \bar{x}(1 - \rho_x) + \rho_x x_t + \sigma_x \varepsilon^x_{t+1} \tag{10}$$

in which $x_t \equiv \log X_t$, $\bar{x}$ is the unconditional mean of x_t, $\rho_x \in (0,1)$ is the persistence coefficient, $\sigma_x > 0$ is the conditional volatility of x_t, and ε^x_{t+1} is an independently and identically distributed (i.i.d.) standard normal shock. The firm-specific productivity for firm i, Z_{it}, has a transition function given by:

$$z_{it+1} = \rho_z z_{it} + \sigma_z \varepsilon^z_{it+1} \tag{11}$$

where $\rho_z \in (0,1)$ is the persistence coefficient, $\sigma_x > 0$ is the conditional volatility of z_{it}, and ε^z_{it+1} is a standard Gaussian shock. Finally, ε^z_{it+1} and ε^z_{jt+1} are uncorrelated for any $i \neq j$, and ε^x_{t+1} and ε^z_{it+1} are uncorrelated for any i.

The firm accumulates capital through investment: $K_{it+1} = I_{it} + (1-\delta)K_{it}$, where i_t stands for investment, and $\delta \in (0,1)$ is the depreciation rate. The adjustment cost of investments is given by:

$$\Phi(I_{it}, K_{it}) = \frac{\theta_{it}}{2}\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} \tag{12}$$

in which $\theta_{it} = \theta^+ \times \mathbb{I}_{I_{it} \leq \delta} + \theta^- \times \mathbb{I}_{I_{it} < \delta}$, and $\theta^- > \theta^+ > 0$ are constant parameters.

The stochastic discount factor, denoted M_{t+1}, is specified exogenously as:

$$M_{t+1} = \beta e^{[\gamma_0 + \gamma_1 (x_t - \bar{x})(x_t - x_{t+1})]} \tag{13}$$

in which $\beta \in (0,1)$ is the time discount factor, and $\gamma_0 > 0$ and $\gamma_1 < 0$ are constant parameters. After observing X_t and Z_{it}, firm i makes optimal investment decision, I_{it}, and optimal exit decision, χ_{it}, to maximize its cum-dividend market equity, denoted V_{it}, given by:

$$V_{it} \equiv V(K_{it}, Z_{it}, X_t) = \max_{\{\chi_{it}\}}\left(\max_{\{I_{it}\}} \Pi_{it} - I_{it} - \Phi(I_{it}, K_{it}) + E_t\left[M_{t+1}V_{it+1}\right], 0\right) \tag{14}$$

When the inner maximand is greater than or equal to zero, firm i stays in the economy, i.e., $\chi_{it} = 0$. Evaluating the value function at the optimum yields $V_{it} = D_{it} + E_t[M_{t+1}V_{it+1}]$, in which $D_{it} \equiv \Pi_{it} - I_{it} - \Phi(I_{it}, K_{it})$, and $E_t[M_{t+1}r^S_{it+1}] = 1$, in which $r^S_{it+1} \equiv V_{it+1}/(V_{it} - D_{it})$ is the stock return.

When the inner maximand is negative, firm i exits at the beginning of t, i.e., $\chi_{it} = 1$. We set its stock return over period $t-1$, r^S, to be a predetermined delisting return, denoted $\tilde{R}$. The exit firm enters an immediate reorganization process. The current shareholders receive nothing and leave. New shareholders take over the firm's capital to form a new firm. For tractability, we assume that the reorganization process occurs instantaneously. At the beginning of period t, the exiting firm is replaced by a new firm with a new firm-specific log productivity of $\bar{z}$, which is its unconditional mean. This parsimonious modeling of entry and exit keeps the number of firms constant (Bai et al., 2019).

We calibrate our model in monthly frequency. Our baseline model has in total 14 parameters shown below:

$$\{\beta, \gamma_0, \gamma_1, \alpha^L, \bar{x}, \rho_x, \sigma_x, \delta, \tilde{R}, \rho_z, \sigma_z, f, \theta^+, \theta^-\}$$

all of which takes the values in Bai et al. (2023) and are reported in Panel A of Table 5. For the extended model, we set $\alpha^H = 1.05$ and $\bar{K} = 15$ for illustrative purposes. We conduct robustness checks for various values of α^H and $\bar{K}$ and the results hold qualitatively.[3]

[Table 5 here]

We compute the average excess returns, annualized and in percentage, of the 10 decile portfolios and the high-minus-low (H-L) portfolio based on the book-to-market ratio and the NEGP ratio, respectively. Panel B reports the returns from the simulated data of the baseline model with $\bar{K} = 0$, and Panel C reports the returns of the model with $\bar{K} = 15$.

Two important observations emerge. First, the high-minus-low NEGP return premium is positive, 2.261% per annum, under the traditional investment model with $\bar{K} = 0$, but turns negative, -2.762%, once a region of IRTS technology is present (i.e., $\bar{k} = 15$) all else equal. Second, the value premium is 4.558% under the model with $\bar{K} = 0$ but drops sharply to 0.697% once IRTS technology is present. The above patterns are consistent with the empirical observations that the value premium gets smaller over time. Next we test the implications on the NEGP premium empirically.

4.4 Empirical evidence

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)

[3]The results on robustness checks are not reported and available upon request.

firms can generate sizable value-weighted returns. Second, the previous cross-sectional return spread cannot be fully explained by the profitability premium. Third, in 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.

4.4.1 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.

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 their characteristics 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 the 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 panels (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. 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.

double sorting 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 4.4.1, 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 assets. Then, for firms in each of these five profitability portfolios, we further classify them into five portfolios based on the firm's 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 reversed for high net-earning bins. Based on these empirical patterns, we can conclude that net earnings at least contain some information about future stock returns that are 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 on 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.

4.4.2 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 Eugene F. Fama and Kenneth R. 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 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 the 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 can 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.

4.4.3 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 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:

$$R_{i,t+1} = \alpha_0 + \beta_1 NI_{i,t} + \beta_2 netXGSA_{i,t} + \Gamma X_{i,t} + \varepsilon_{i,t+1} \tag{15}$$

Throughout this section, i and t refer 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 2.3. The momentum variable is calculated as the average stock return between the past 1 month and 12 months. Same as before, all the t-statistics are adjusted by the 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 of 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, and 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 the 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 the 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 the 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, the 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 the firm's monthly expected stock returns.

5 Conclusion

Using the firm-level data on the accounts of all publicly traded firms, we study the evolution of the shape of production function. Our investigation uncovers a noteworthy shift since 1980, as the corporate production function transitions towards a sigmoidal (or convex-concave) configuration, with the convexity factor progressively gaining prominence over the years. Additionally, our analysis demonstrates that this enduring trend is pervasive across diverse industries and advanced economies. We then leverage this empirical evidence to explore the broader implications of the altered corporate production function on the macroeconomic landscape. Our main focus is directed toward the surge in popularity of firms with negative net earnings, the origins of market power, and intriguingly distinct implications for asset pricing.

The assumption of a concave production function stands as a fundamental cornerstone within the realm of economic literature. Our findings give rise to various avenues for potential future research. Most notably, our results challenge the conventional wisdom by revealing a departure from the standard macroeconomic models, which fail to accommodate long-term shifts in the aggregate production function's shape. This notable deviation from predictions since the early 1980s prompts us to anticipate the development of fresh frameworks and analytical perspectives that could prove invaluable for contemplating these evolving trends.

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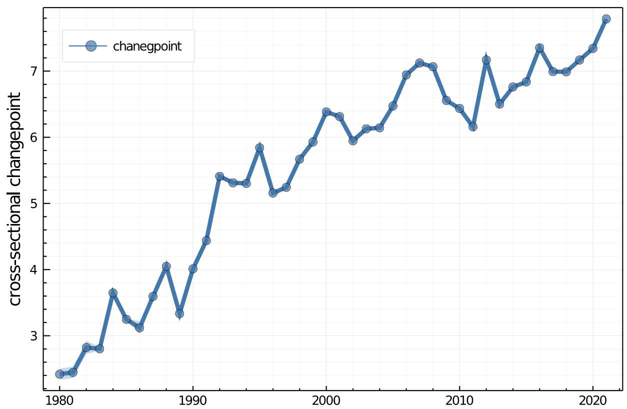
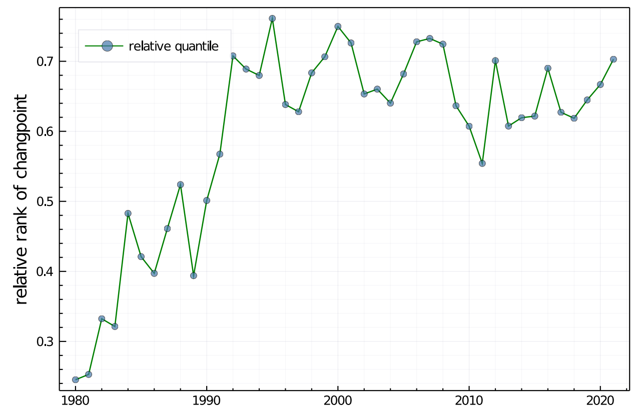
Figure 1: Long-run Changes in Corporate Production Function: Baseline Evidence

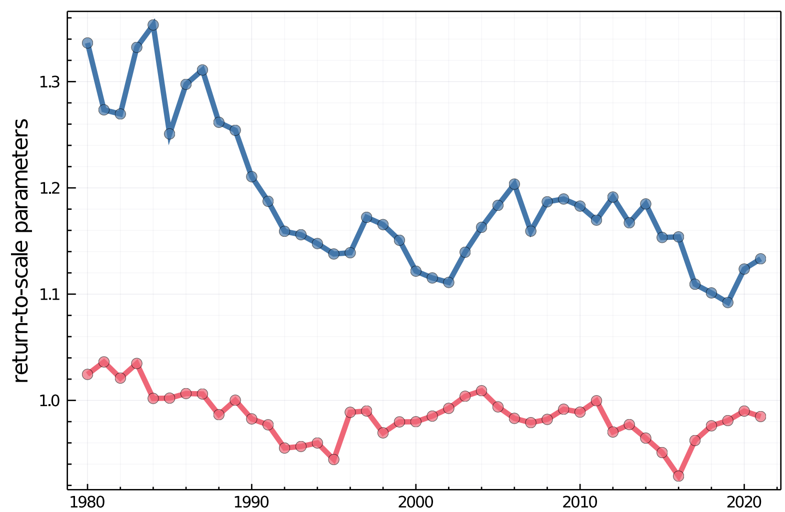
(a) changepoint



(b) relative rank

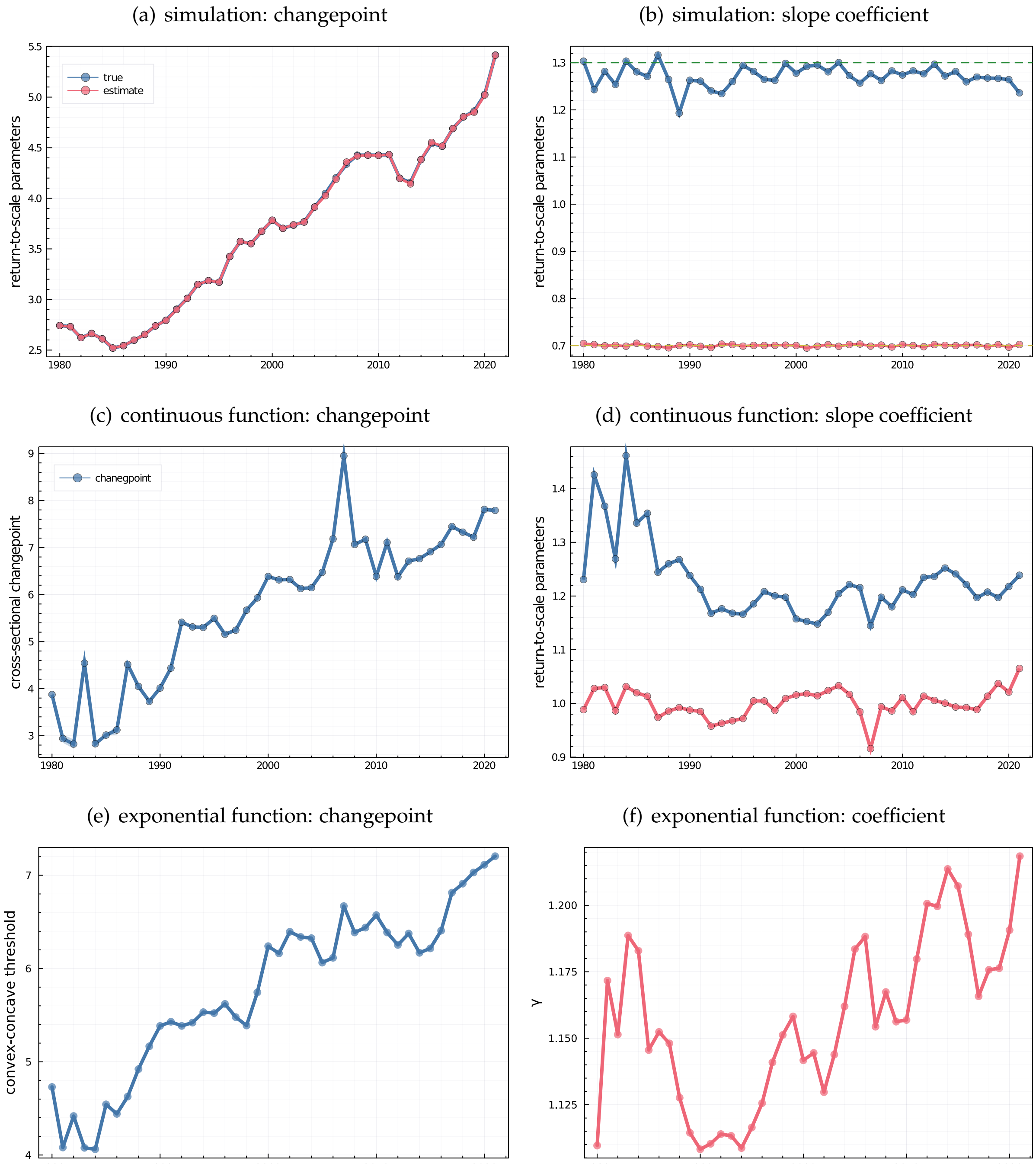


(c) slope coefficient



Notes: Graph (a) shows the estimated cross-sectional changepoints using Bayesian MCMC. The band shows the 95% credible interval approximated with two times posterior standard deviations. Graph (b) shows the relative ranks of the estimated cross-sectional changepoints using Bayesian MCMC. Graph (c) shows the estimated slope coefficients, and the blue and red curves indicate $\hat{\beta}_{at}$ and $\hat{\beta}_{et}$, respectively. The baseline model specification is shown in Equation (2) with y being total output (Compustat data item *SALE*) and k the sum of physical capital (Compustat data item *PPENT*) and intangible capital. We measure the stock of intangible capital by following Peters and Taylor (2017). Data is obtained from *Compustat*.

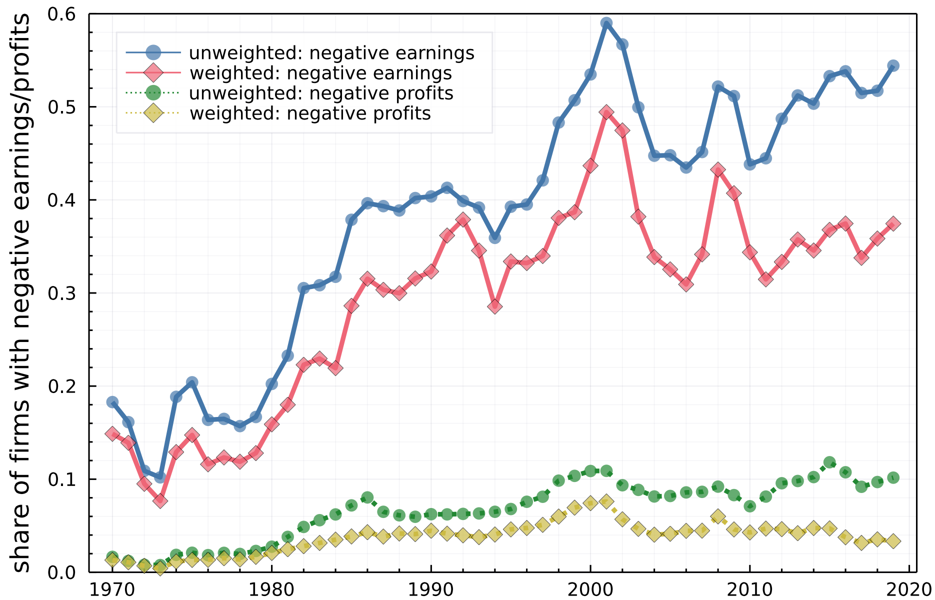
Figure 2: Long-run Changes in Corporate Production Function: Robustness Checks



Notes: Graph (a) compares the simulated true and estimated changepoints $\bar{k}_t$ obtained from Bayesian MCMC. The blue curve represents the true value, while the red represents the estimation. Graph (b) shows the corresponding estimated slope coefficients, and the green and orange dashed lines indicate the true values: 1.3 and 0.7. The blue curve represents the estimated time series $\hat{\beta}_{at}$ and the red curve represents the estimated time series $\hat{\beta}_{et}$. Graphs (c) and (d) report the estimated changepoints and slope coefficients for continuous production function shown as in Equation (5). Meanwhile, Graph (e) and (f) report the corresponding results for using the exponential functional form shown as in Equation (6). Across all these three model specifications, total output y is measured as Compustat data item *SALE* and capital stock k is the sum of physical capital (Compustat data item *PPENT*) and intangible capital, where we measure the stock of intangible capital by following Peters and Taylor (2017). Data is obtained from *Compustat*.

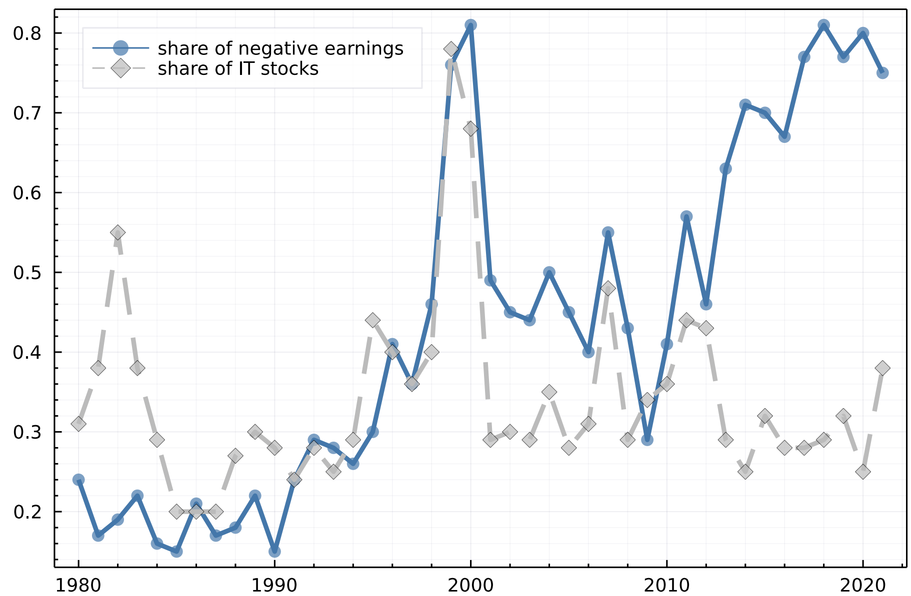
Figure 3: Changing Production Function: Industry-level Evidence

Figure 4: The Rise of Firms with Negative Net Earnings



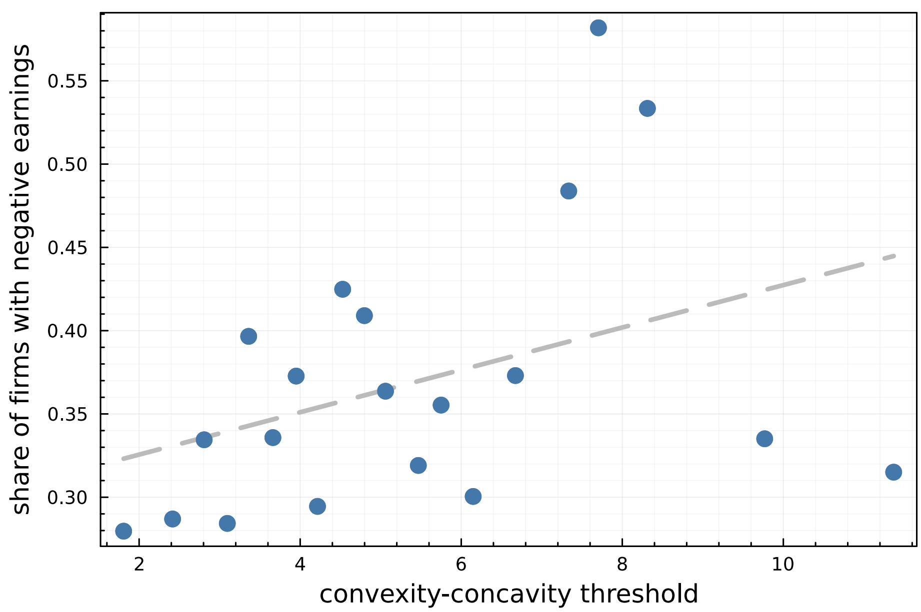
Notes: This figure presents the time-series plot of the fraction of unprofitable public firms. In each year, we count the number of firms with negative profits and divide it by the total number of firms. We use two different profitability measures – gross profits (Compustat data item *GP*) and net earnings (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 5: The Rise of IPOs with Negative Net Earnings



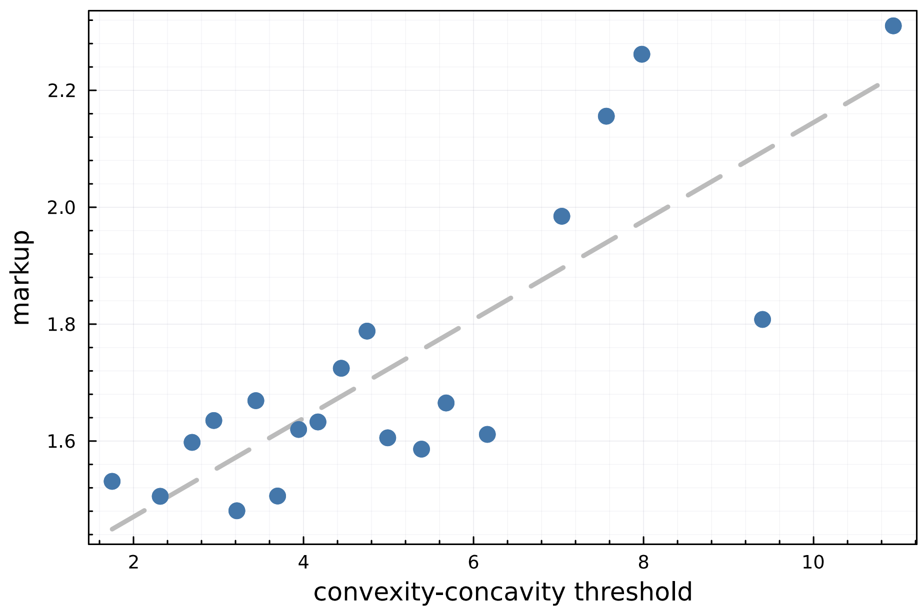
Notes: This figure presents the time-series plot of the fraction of unprofitable IPOs. In each year, we count the number of IPOs with negative net earnings and divide it by the total number of IPOs. The information related to corporate earnings is measured at the most recent twelve months before going 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 6: Binscatter Plot between Convexity-Concavity Threshold and Share of Firms with Negative Net Earnings



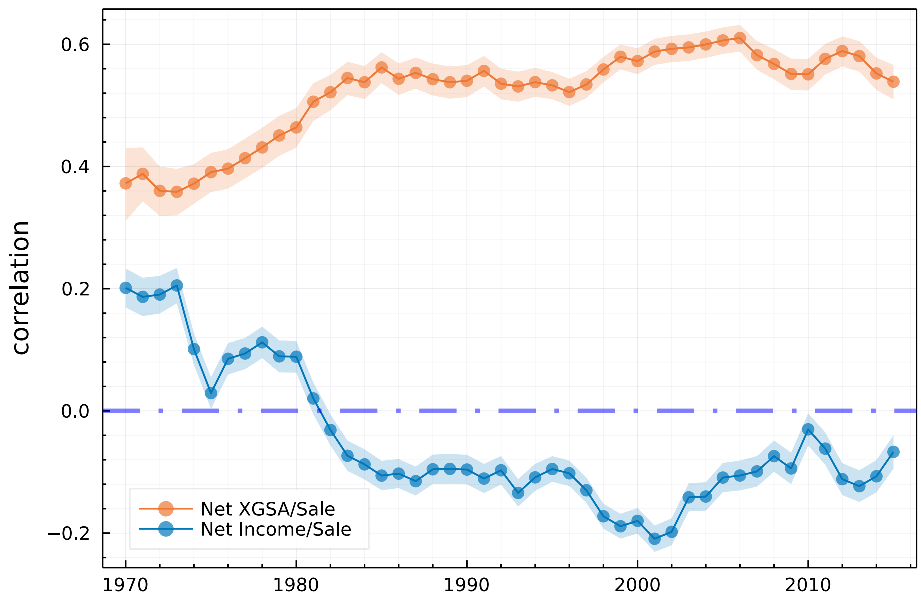
Notes: This figure presents the binscatter plot between the industry-level turning point for the convexity-concavity production function and the share of firms with negative earnings. The gray dashed line represents the linear-fit regression. Specifically, for each year and each industry, we obtain the empirical measures of turning point with our baseline approach. 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 7: Binscatter Plot between Convexity-Concavity Threshold and Market Power



Notes: This figure presents the binscatter plot between the industry-level turning point for convexity-concavity production and markup. The gray dashed line represents the linear-fit regression. Specifically, for each year and each industry, we obtain the empirical measures of turning point with our baseline approach. In addition, for each industry in each year, we first obtain the firm-level markup measured by following De Loecker, Eeckhout and Unger (2020)'s approach and then calculate the industry-level mean. Data is obtained from *Compustat*.

Figure 8: 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*.

Table 1: **Time series averages of by-industry estimates**

industry	$\bar{k}$	α_a	α_e	β_a	β_e	σ_1^2	σ_2^2	$\beta_a - \beta_e$
				baseline				
All	5.53	-1.53	-0.27	1.19	0.99	1.74	0.46	0.2
	$[5.53, 5.53]$	$[-1.55, -1.51]$	$[-0.29, -0.24]$	$[1.18, 1.19]$	$[0.98, 0.99]$	$[1.73, 1.75]$	$[0.45, 0.46]$	$[0.20, 0.21]$
				by industry				
1	4.12	-0.7	0.21	1.05	0.94	1.44	0.22	0.1
	$[4.08, 4.18]$	$[-0.77, -0.63]$	$[0.17, 0.25]$	$[1.01, 1.09]$	$[0.94, 0.95]$	$[1.39, 1.49]$	$[0.22, 0.23]$	$[0.07, 0.14]$
2	4.15	-0.5	0.15	0.91	0.96	1.58	0.17	-0.05
	$[4.11, 4.19]$	$[-0.58, -0.42]$	$[0.1, 0.18]$	$[0.87, 0.96]$	$[0.96, 0.97]$	$[1.52, 1.64]$	$[0.16, 0.18]$	$[-0.09, -0.01]$
3	4.48	-1.06	0.06	1.15	0.96	1.42	0.2	0.2
	$[4.47, 4.49]$	$[-1.12, -1.01]$	$[0.03, 0.09]$	$[1.13, 1.17]$	$[0.95, 0.96]$	$[1.39, 1.45]$	$[0.2, 0.2]$	$[0.18, 0.22]$
4	6.19	-1.46	-0.79	0.98	1.03	1.57	0.39	-0.05
	$[6.08, 6.3]$	$[-1.51, -1.4]$	$[-0.86, -0.72]$	$[0.96, 1]$	$[1.02, 1.04]$	$[1.53, 1.6]$	$[0.37, 0.41]$	$[-0.07, -0.03]$
5	4.09	-1.17	-0.63	1.08	1.01	1.57	0.33	0.08
	$[4.08, 4.1]$	$[-1.21, -1.13]$	$[-0.66, -0.6]$	$[1.06, 1.1]$	$[1, 1.01]$	$[1.55, 1.6]$	$[0.32, 0.33]$	$[0.06, 0.09]$
6	6.57	-0.49	-0.41	0.83	0.95	1.4	0.25	-0.12
	$[6.52, 6.61]$	$[-0.56, -0.42]$	$[-0.48, -0.34]$	$[0.79, 0.86]$	$[0.94, 0.96]$	$[1.34, 1.45]$	$[0.24, 0.26]$	$[-0.16, -0.09]$
7	4.53	-0.52	0.12	1.1	1.01	1.23	0.33	0.09
	$[4.42, 4.65]$	$[-0.58, -0.46]$	$[0.07, 0.16]$	$[1.08, 1.13]$	$[1, 1.02]$	$[1.17, 1.28]$	$[0.33, 0.34]$	$[0.07, 0.13]$
8	6.44	-1.54	-0.14	0.98	0.93	1.9	0.3	0.05
	$[6.42, 6.46]$	$[-1.59, -1.5]$	$[-0.22, -0.07]$	$[0.97, 1]$	$[0.92, 0.94]$	$[1.88, 1.92]$	$[0.29, 0.31]$	$[0.03, 0.07]$
9	5.95	-0.11	-0.16	0.83	0.9	1.09	0.21	-0.08
	$[5.74, 6.15]$	$[-0.2, -0.03]$	$[-0.22, -0.09]$	$[0.79, 0.86]$	$[0.9, 0.91]$	$[1.02, 1.17]$	$[0.21, 0.22]$	$[-0.11, -0.04]$
10	9.98	-0.9	-0.02	0.93	0.8	1.66	0.42	0.13
	$[9.92, 10.06]$	$[-0.92, -0.87]$	$[-0.1, 0.06]$	$[0.92, 0.93]$	$[0.79, 0.81]$	$[1.64, 1.68]$	$[0.41, 0.44]$	$[0.12, 0.14]$

Notes: This table reports the time-series averages of the parameters in the baseline model and by-industry model. Each column shows the time-series average of one of the parameters. The last column compares the two slope coefficients. Numbers in parentheses are the lower and upper 2.5% posterior percentiles obtained from 20,000 draws.

Table 2: Reduced-form Evidence: Convexity-Concavity Threshold and Share of Firms with Negative Net Earnings

	share of firms with negative earnings			
	(1)	(2)	(3)	(4)
Threshold	0.012***	0.007*	0.019***	0.010***
	(3.674)	(1.786)	(7.388)	(3.525)
Year		Yes		Yes
Industry			Yes	Yes
N	420	420	420	420
Adjusted R^2	0.029	0.070	0.695	0.799

Notes: This table presents the association between industry-level convexity-concavity threshold and the share of firms with negative earnings with different fixed-effect model specifications. Specifically, for each year and each industry, we obtain the empirical measures of turning point with our baseline approach. 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 the industry-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 3: Reduced-form Evidence: Convexity-Concavity Threshold and Markup

	markup			
	(1)	(2)	(3)	(4)
Threshold	0.087***	0.075***	0.067***	0.020**
	(11.040)	(8.351)	(8.268)	(2.020)
Year		Yes		Yes
Industry			Yes	Yes
N	360	360	360	360
Adjusted R^2	0.252	0.228	0.611	0.665

Notes: This table presents the association between industry-level convexity-concavity threshold and markup with different fixed-effect model specifications. Specifically, for each year and each industry, we obtain the empirical measures of turning point with our baseline approach. In addition, for each industry in each year, we first obtain the firm-level markup measured by following De Loecker, Eeckhout and Unger (2020)'s approach and then calculate the industry-level mean. Original data used in this table is at the industry-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: 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 × 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 2.3. Data used in this table is at firm-year level and obtained from *Compustat*. We introduce firm- and year-fixed effects in columns (1)-(10). In column (11), we include industry- and year-fixed effects. 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 5: Model Parameters and Cross-sectional Return Moments

Panel A: Estimated parameters											
β	γ_0	γ_1	α^L	$\bar{x}$	ρ_x	σ_x	δ	$\tilde{R}$	ρ_z	σ_z	f
0.9999	18	-450	0.70	-3.98	0.72117	0.01643	6.86%/12	-24.53%	0.97	0.2152	0.0496
θ^+	θ^-	α^H	$\bar{K}$								
0.1385	102.2631	1.05	15								
Panel B: Average excess returns with $\bar{K} = 0$											
	Low	2	3	4	5	6	7	8	9	High	H-L
$\bar{R}_{value}$	9.945	10.565	11.026	11.213	11.747	11.754	12.415	12.499	13.035	14.503	4.558
$\bar{R}_{NEGP}$	12.633	12.586	12.398	11.980	11.657	11.072	10.592	10.573	14.836	14.894	2.261
Panel C: Average excess returns with $\bar{K} = 15$											
	Low	2	3	4	5	6	7	8	9	High	H-L
$\bar{R}_{value}$	10.925	11.475	11.840	12.061	12.232	12.351	12.321	12.242	12.010	11.622	0.697
$\bar{R}_{NEGP}$	13.181	12.894	12.741	12.523	12.241	11.998	11.713	11.427	10.991	10.419	-2.762

Notes: This table presents the calibrated model parameters in Panel A and average excess returns of the 10 decile portfolios and the H-L portfolio sorted based on book-to-market (labeled as $\bar{R}_{value}$) and net-earnings-to-gross-profitability ratios (labeled as $\bar{R}_{NEGP}$), respectively, in Panels B and C for the baseline and the one with $\bar{K} = 15$. β is the time discount factor, γ_0 and γ_1 are the constant in the stochastic discount factor, α^L is the DRTS curvature parameter in the production function, $\bar{x}$, ρ_x, and σ_x are the unconditional mean, persistence, and conditional volatility of aggregate productivity, δ is depreciation, $\tilde{R}$ is exit return, ρ_z and σ_z are the persistence and conditional volatility of firm-specific productivity, f is fixed operation cost, θ^+ and θ^- are investment adjustment costs parameters when investment rate is above and below the depreciation rate, α^H is the IRTS curvature parameter in the production function, and $\bar{K}$ is the threshold capital below which production technology exhibits ITCS and, above which, DRTS. Parameters are calibrated in monthly frequency. Returns are annualized and in percentage, which are averaged across 100 simulated panels, each with 3,500 firms and 1,000 months (with the first 300 months discarded).

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 2.3. 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 ($\frac{\mathrm{NI}}{GP}$) + Gross Profitability ($\frac{\mathrm{GP}}{AT}$)

(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 2.3. 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). Parts I and II report the results for the full sample, meanwhile, Parts III and IV present the corresponding outcomes in a subsample excluding microcap 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*.

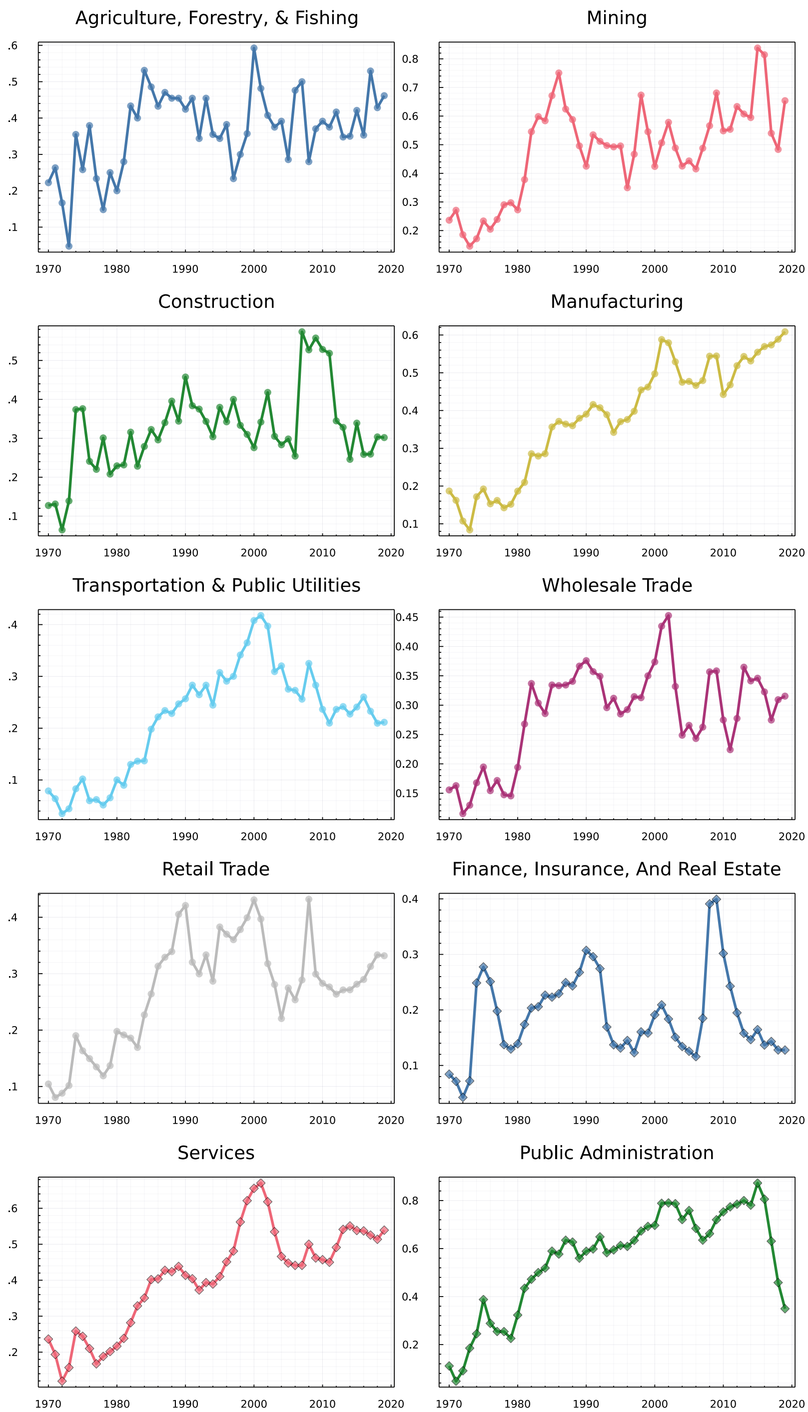
Table 8: Fama-MacBeth Regressions of Future Returns on Net Income and Customer Capital Expenses

	(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 2.3, 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*.

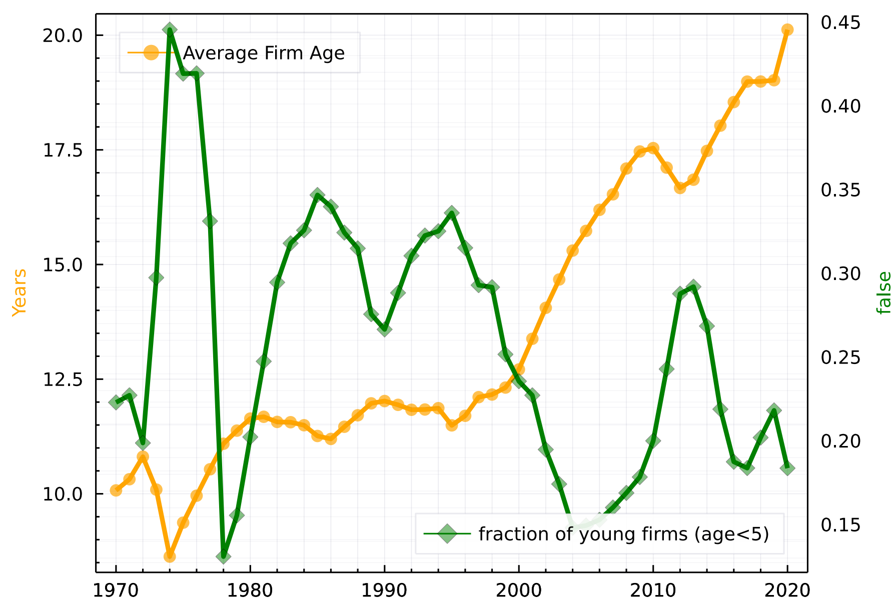
Online Appendix

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



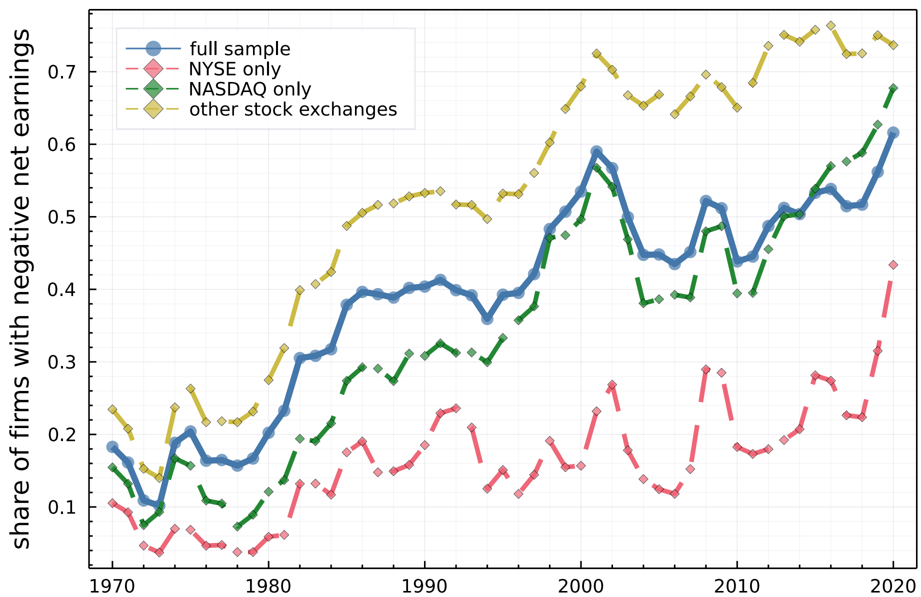
Notes: This figure presents the time-series plot of the fraction of unprofitable public firms in different industries. In each year, for each industry, we count the number of firms with negative net earnings and divide it by the total number of firms. Ten industries are defined as follows: Agriculture, 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 the 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 an 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*.

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: Double Sorting: Equal-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	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 ($\frac{\text{GP}}{AT}$)

(E): Raw excess return (%)

		Gross Profitability						
		Low	2	3	4	High	Low-High	(t-stat)
	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)
Customer Capital Expenses	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)
	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)
Customer Capital Expenses	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)
	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)
Customer Capital Expenses	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)
	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)
Customer Capital Expenses	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 ($\frac{\mathrm{NI}}{GP}$) + Gross Profitability ($\frac{\mathrm{GP}}{AT}$)

(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 ($\frac{\text{net XGSA}}{GP}$) + Gross Profitability ($\frac{\text{GP}}{AT}$)

(M): Raw excess return (%)

		Gross Profitability						
		Low	2	3	4	High	Low-High	(t-stat)
Customer Capital Expenses	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)
	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)
Customer Capital Expenses	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)
	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)
Customer Capital Expenses	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)
	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)
Customer Capital Expenses	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)
	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 2.3. 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, Parts III and IV present the corresponding outcomes in a subsample excluding microcap 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*.