The Utilization Premium*

Fotis Grigoris and Gill Segal

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Abstract

Firms that underutilize their capital are riskier. An investment strategy that longs (shorts) equities with low (high) utilization rates earns 5% p.a. We reconcile this novel utilization premium quantitatively using a production model. Beyond explaining the premium, the model suggests that flexible utilization is key for matching the cross-sectional distribution of investment and stock prices jointly. A model without flexible utilization yields many counterfactuals, such as investment's dispersion being too low, and its skewness bearing the wrong sign. Flexible utilization can address these moments by making depreciation rates fluctuate endogenously. Overall, utilization tightens the link between firms' production and valuation.

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*Grigoris: Kelley School of Business, Indiana University, Hodge Hall, Bloomington, IN 47405, U.S.A. (e-mail: `fgrigori@iu.edu`); Segal (corresponding author): Kenan-Flagler Business School, University of North Carolina at Chapel Hill, McColl Building, Chapel Hill, NC 27599, U.S.A. (e-mail: `Gill_Segal@kenan-flagler.unc.edu`). This paper benefited from comments and suggestions by Max Croce, Ric Colacito, Eric Ghysels, Erik Loualiche (discussant), Christian Lundblad, Jun Li (discussant), Dimitris Papanikolaou, Nick Roussanov, Jincheng Tong (discussant), Miao Ben Zhang (discussant), Harold Zhang, and seminars participants at the 2019 MFA annual meeting, 2019 Northern Finance Association meeting, 2019 Fall UT Dallas Finance Conference, 2020 RAPS Winter Conference, and the University of North Carolina at Chapel Hill. All errors are our own.

Capacity utilization measures the extent to which a business uses its production potential. Flexible capacity utilization lets firms scale their production by choosing how much of their machinery to operate. For instance, instead of decreasing production by selling machines, the firm can choose to keep some machines idle. While existing studies in macroeconomics demonstrate the ability of aggregate-level utilization to predict the business cycle, the extent to which granular-level (i.e., firm or industry level) utilizations quantitatively affect risk and investment remains largely unexplored. In this paper we examine this relationship both empirically and theoretically, and show that it is not only sizable, but also bears important implications for reconciling the joint distribution of cross-sectional real quantities and prices.

First, we show that lower utilization is associated with a substantially higher risk premium in the cross-section of equities. Second, we explain this relation quantitatively in a production economy that emphasizes the role of flexible utilization for both the intertemporal choice of capital and the costs of downscaling. Third, we show that flexible utilization is crucial for production models with real options to jointly target cross-sectional investment moments and high risk premia spreads. Our findings suggest that when utilization changes from fixed to flexible, the dispersion and skewness of investment rates rise, in line with the data. This increases the dispersion of firms' exposures to aggregate productivity. Thus, a model with flexible utilization can generate large cross-sectional variation in expected returns (e.g., a sizable value premium), without relying on high exogenous capital adjustment costs.

Empirically, we start by establishing two novel facts. Using capacity utilization data for a cross-section of industries, we establish that firms that belong to low capacity utilization industries earn an average annual return that is 5.7% higher than the annual return earned by firms that belong to high capacity utilization industries. We term this return spread as the *Utilization Premium*. Moreover, we show that there exists a monotonically decreasing relation between utilization rates and aggregate productivity exposures. The low utilization portfolio has a higher aggregate productivity beta than the high utilization portfolio.

While the baseline utilization premium is based on industry-level return data, the premium is not simply capturing cross-sectoral heterogeneity. We show this in four main ways. First, the spread exists *within* economic sectors. For instance, an economically large utilization spread emerges among durable manufacturers only. Moreover, utilization negatively forecasts future excess returns in predictive regressions that control for sectoral fixed effects. Second, we construct proxies for firm-level utilization rates using Compustat data. The utilization premium remains positive when sorting *firms* into portfolios based on these novel firm-level utilization proxies. Third, we show the utilization spread persists when we form portfolios using the *growth* rate of utilization, thereby eliminating any industry-specific fixed effects in utilization's level. Lastly, through the lens of our model, we show that ex-ante heterogeneity in depreciation or adjustment cost parameters between firms contributes only marginally to the utilization premium.

The utilization premium is distinct from potentially related production-based spreads. Fama and MacBeth (1973) regressions and double sort analyses show that utilization's explanatory power for risk premia is incremental to key characteristics, such as investment and hiring, book-to-market, productivity, financing costs, and intangible capital. The utilization spread is a robust feature of the data. Using different breakpoints, or a different timespan to form portfolios shows that low utilization industries still command higher risk premia.

To rationalize our empirical findings, we incorporate the realistic feature of a flexible utilization decision into a real business-cycle model. When calibrated, the model is able to quantitative replicate both empirical facts. The model-implied firm-level utilization premium is about 5% per annum, matching precisely the empirical counterpart that is based on firm-level utilization proxies. To parallel the model with the industry-based evidence, we also group simulated firms into industries. The model-implied industry-level utilization premium is about 4%, and falls within the confidence interval of the empirical industry-level spread.

In the model, firms extend their production capacity by buying capital and decrease it by selling machines in the secondary market for capital. This market involves frictions. Specifically, the model features a fixed cost for capital disinvestment that makes selling machines a real option. The key ingredient in our model is a variable capacity utilization rate that controls the extent to which installed capital is utilized. Increasing the utilization rate is costly, as it makes capital depreciate faster.[1]

[1] We consider an extension of our model in which the depreciation rate of a firm depends not only on its utilization choice, but also on exogenous depreciation shocks. Allowing for exogenous shocks to depreciation

In an economy in which the capacity utilization rate is fixed, firms can only reduce the cyclicality of their payouts via investment decisions. If adjusting capital is costly, then the risk of each firm is determined entirely by the interaction between aggregate productivity and these capital adjustment costs.[2] With flexible utilization, firms have an additional mechanism to decrease the cyclicality of productivity shocks on payouts.

To illustrate how utilization is tied to firms' risk, consider an economy featuring convex and symmetric capital adjustment costs. A firm operating in a low productivity state has the incentive to reduce its capital, thereby exposing itself to potentially large adjustment costs. Simultaneously, the firm has an incentive to lower its capacity utilization rate. By lowering utilization the firm reduces its capital depreciation rate. This reduced depreciation not only conserves capital for future states that are more productive, but also reduces the adjustment cost of downsizing.[3] By similar logic, increasing utilization in good states reduces the adjustment cost for expanding capital by increasing depreciation. Thus, utilization and investment comove positively. This implies that both very high and very low utilization firms have high exposures to aggregate productivity. Both extremes reflect firms that incur high risk by desiring to modify their capital stock to a large extent under adjustment costs. Simultaneously altering utilization partially hedges their (dis)investment policies.

Two mechanisms break the symmetry between high and low utilization firms. First, with a positive fixed adjustment cost disinvestment becomes a costly real option. Firms with moderately low levels of productivity substitute disinvestment by lowering utilization. Instead of selling capital, firms temporarily downscale by reducing the utilization of installed machines. As the friction in the market for selling capital is higher for these firms, they are riskier. Second, the model features a countercylical market price of risk (motivated by countercylical volatility). Thus, firms' whose valuations covary more with economic conditions during bad states command a larger risk premium. During bad states, low utilization firms

induces only a small quantitative effect on the results, highlighting the importance of endogenous utilization.

[2]Firms that disinvest (invest) the most in low (high) aggregate productivity states are required to pay large capital adjustments costs. Consequently, since these firms are unable to fully absorb the impact of productivity shocks on their payouts, these firms are risky.

[3]In other words, lower utilization implies that the current depreciation, δ_t, falls. With quadratic adjustment frictions over net investment, the adjustment cost is proportional to the distance between i_t, the investment rate, and δ_t. As δ_t drops whenever i_t drops, the adjustment cost falls.

are those with the higher productivity betas, and earn higher expected returns.

Our theoretical results suggest that flexible capacity utilization plays a pivotal role for simultaneously matching investment and asset-pricing moments in the presence of real investment options. In the model, whenever utilization is fixed, the cross-sectional dispersion and skewness of investment are less than half of their empirical magnitudes. The time-series skewness of firm-level investment is negative, whereas it is positive in the data. This happens because disinvestment in the model is a costly real option. During moderate economic slowdowns, firms "wait and see" if productivity will improve before opting to sell capital. Under fixed utilization, these firms do not alter their capital stocks and set their investment rates equal to the (constant) depreciation rate instead. Because a mass of waiting firms are then lumped around the center of investment's distribution, the cross-section of investment rates is compressed, and features low dispersion. If productivity is persistently negative, these waiting firms pass a tipping point in which they are overly burdened with unproductive capital, and disinvest sharply. These disinvestment jumps create the counterfactual negative sign for the time-series skewness of investment. As the distribution of investment rates is too compressed, firms' risk exposures to aggregate productivity do not feature enough heterogeneity, which shrinks investment-related spreads such as the value premium.

Introducing flexible utilization to the model addresses the former model misses. When utilization is flexible, firms can also respond to moderate drops in productivity by utilizing less capital. This causes depreciation to fall, and reduces the investment required to preserve the current capital stock. Since the natural (or preservation) rate of investment in this economy is time-varying, even firms that "wait and see" have to keep altering their investment rates to preserve their existing capital. Thus, the long periods of constant investment rates are eliminated. Time-varying depreciation rates that are (ex-post) heterogeneous between firms increase the cross-sectional dispersion of investment. This is because waiting firms are no longer massed at the same investment rate. Moreover, since firms utilize their machines more intensively in good times, depreciation increases in these periods. Larger investments are needed to expand capital, causing the time-series and cross-sectional skewness of investment to rise, turn positive, and match the data. Lastly, greater dispersion in investment rates suggest a larger dispersion in firms' risk exposures, which boosts cross-sectional spreads.

The problem of matching moments under fixed utilization is not alleviated by recalibrating the model. For instance, the diminished value premium in the model with fixed utilization can be raised by increasing the convex capital adjustment costs. However, the adjustment costs required to match the value premium with fixed utilization are 100% higher than those with flexible utilization. This alternative calibration has counterfactual implications for investment's dispersion.

Lastly, our model suggests that firms' depreciation and utilization rates should comove positively. We confirm this prediction in the data and explore its implications. We demonstrate that utilization is useful for measuring depreciation rates. Recent macro-finance studies suggest that BEA- and Compustat-based depreciations exhibit a low correlation, leading to different distributions of gross investment rates. We show that utilization shrinks the wedge between BEA- and Compustat-implied depreciation rates. While the correlation between the two is only 3%, this correlation increases to 14% when accounting for utilization fluctuations. Motivated by this finding, we illustrate a theoretically-motivated method to measure depreciation rates that is based on utilization data. The method allows us to compute depreciation at a higher frequency than existing data sources.

Taken together, our empirical and theoretical results emphasize the economically important relation between capacity utilization, investment, and risk premia, and tighten the connection between firms' production dynamics and their valuations.

The paper proceeds as follows. Section 1 reviews the related literature. Section 2 establishes the novel empirical facts. Section 3 a model with flexible utilization rates to rationalize these findings. Section 4 examines the relation between utilization and risk premia through the lens of the model. Section 5 explores the theoretical implications of flexible utilization for investment dynamics and adjustment costs. Section 6 provides concluding remarks.

1 Related literature

The paper contributes to the literatures on the role of capacity utilization in RBC models, costly reversibility, and production-based asset pricing.

Our paper is tied to studies that examine the effects of time-varying capacity utilization in the macroeconomic literature. As a leading indicator, aggregate utilization data is studied extensively in relation to business cycle fluctuations. For instance, prior studies show how variable utilization is useful for matching macroeconomic growth dynamics to the data (e.g., Greenwood, Hercowitz, and Huffman (1988), and Jaimovich and Rebelo (2009)). Additionally, Burnside and Eichenbaum (1996) show that variable utilization rates can propagate shocks over the business cycle, and amplify the impact of technology shocks. The macroeconomic literature utilizes several empirical proxies for utilization. Burnside, Eichenbaum, and Rebelo (1995) use electricity usage, while Basu, Fernald, and Kimball (2006) use hours per worker to proxy for all unobserved intensive margins. Similar to our empirical approach, Comin and Gertler (2006) use the FRB's measure of capacity utilization to study business cycle fluctuations over the medium-term.

In contrast to the macroeconomic literature, the relation between capacity utilization and asset prices has received considerably less attention. This is despite the fact that capacity utilization is conceptually related to firm-level production decisions, and despite the fact that the FRB regularly reports granular data on the cross-section of utilization rates for various manufacturing and mining industries, and utilities.[4]

Of the small set of papers that also study capacity utilization in the context of asset pricing, most focus on aggregate asset-pricing moments. For instance, Garlappi and Song (2017) include capacity utilization in a general equilibrium production-based asset pricing model and show that varying utilization is important to reconcile the market price of risk of investment-specific technology (IST) shocks with the data. Da, Huang, and Yun (2017) use industrial electricity usage as a proxy for utilization and find that higher electricity usage in the current period predicts lower stock market returns in the future. This latter result is broadly consistent with our utilization premium, but the findings in Da et al. (2017) pertain to the time-series of market returns rather than the cross-section of equities that we study.

The model in Cooper, Wu, and Gerard (2005) focuses on explaining the value premium and also includes capacity utilization. Although the authors find a *qualitatively* negative

[4]While the U.S. manufacturing sector is of modest size, the sector still influences the macroeconomy to a large degree (Andreou, Gagliardini, Ghysels, and Rubin, 2019). Consequently, capacity utilization figures are routinely analyzed by both the Federal Reserve Bank (FRB) and other market participants.

relation between utilization and industry-level stock returns using OLS regressions in their empirical analysis, we emphasize the *quantitative* contribution of capacity utilization to cross-sectional risk premia. We do this both theoretically, via a calibrated model, and empirically, by establishing a novel spread. The utilization spread is distinct from the value premium, and a host of other production-based characteristics.

The notion of costly reversibility – the assumption that firms face higher costs to contract rather than expand their capital stocks – continues to influence research in macroeconomics and finance.[5] In macroeconomics, recent studies such as Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) combine costly reversibility and uncertainty shocks to explain the dynamics of real quantities over the business cycle. In finance, costly reversibility has become standard in many models rationalizing patterns in expected returns.

The studies of Zhang (2005), Carlson, Fisher, and Giammarino (2004) and Cooper (2006), among others, explain the value premium and other cross-sectional spreads by assuming that capital is partially irreversible. Recent literature debates on whether these canonical models can produce realistic distributions of investment rates and risk premia jointly. While Clementi and Palazzo (2019) present evidence that investment is not as irreversible as these models suggest, and show that disinvestment is quite prevalent, Bai, Li, Xue, and Zhang (2019) show that few firms disinvest capital, which supports the assumption of irreversibility. The two studies differ in their measurement of gross investment rates.[6]

The importance of utilization for jointly matching investment and prices extends beyond these two studies. While Clementi and Palazzo (2019) and Bai et al. (2019) reach opposite conclusions regarding the importance of costly reversibility, neither study considers the frictions generated by costly real investment options. In contrast, our study shows that real options (particularly those to disinvest) are quantitatively important for (i) matching the magnitude of the utilization premium, (ii) producing a realistic correlation between utilization and investment rates, and (iii) capturing the negative impact of uncertainty shocks on

[5]While the literature on costly reversibility is voluminous, some key studies include Dixit and Pindyck (1994), Abel and Eberly (1996), and Cooper and Haltiwanger (2006).

[6]Specifically, in Clementi and Palazzo (2019) gross investment rates are measured using industry-level depreciation rates from the Bureau of Economic Analysis. In Bai et al. (2019) gross investment rates are measured using firm-level depreciation expenses from Compustat.

investment as shown in Bloom (2009). In the presence of real options, flexible utilization is key for producing a realistic distribution of model-implied investment rates and sizable risk premia. This conclusion is not driven by how gross investment is measured, but by the inherent properties of the model. Beyond matching many of the same moments as Bai et al. (2019) and Clementi and Palazzo (2019), our model also matches higher-order time-series moments of investment rates, such as the time-series skewness of investment.

More broadly, our paper is related to asset-pricing studies that connect production economies to expected returns and interest rates (e.g., Belo and Lin (2012), Van Binsbergen, Fernández-Villaverde, Koijen, and Rubio-Ramírez (2012), Jones and Tuzel (2013), Ai and Kiku (2016), Belo, Li, Lin, and Zhao (2017), Kilic (2017), Tuzel and Zhang (2017), Ai, Li, Li, and Schlag (2019), Dou, Ji, Reibstein, and Wu (2019), Loualiche et al. (2019)). The relation between utilization and asset prices is of particular interest to this growing literature that examines the joint dynamics of firm-level investment and dispersion in risk premia.[7]

Prior studies in this literature include Belo, Lin, and Bazdresch (2014), who study the impact of labor market frictions on asset prices and find that firms with low hiring rates earn high returns. We show empirically that hiring rates are indistinguishable between low and high utilization industries. Likewise, neither differences in intangible capital (e.g., Eisfeldt and Papanikolaou (2013)) nor financing costs (e.g., Belo, Lin, and Yang (2018)) explain the utilization premium. Imrohoroglu and Tuzel (2014) examine firm-level total factor productivity (TFP), and theoretically and empirically show that low TFP firms earn a significant productivity premium. This is important for our study because TFP and capacity utilization are linked by the fact that TFP can be decomposed into three distinct components: utilization, markups, and technology. While utilization is a component of TFP, we show empirically that most of the productivity premium stems from the technology and markup components of TFP. That is, controlling for capacity utilization, the productivity premium persists. Conversely, the utilization spread also persists after controlling for TFP.

Recently, Aretz and Pope (2018) estimate firm-level capacity overhang, or the difference between a firm's installed and optimal capital stock, and show that overhang has sizable

[7] In a similar strand of literature, Ai, Kiku, Li, and Tong (2018) examine firm-level outcomes, such as investment and dividends, in a model featuring production and dynamic contracting.

implications for cross-sectional risk premia. Although capacity utilization and overhang are conceptually similar, we show that these margins result in theoretically and empirically distinct spreads. In particular, both portfolio double sorts and Fama and MacBeth (1973) regressions show that the utilization spread survives controlling for overhang, and vice versa.

In all, we contribute to the production-based asset pricing literature by focusing on the utilization rate of productive units. We demonstrate that capacity utilization is an important determinant of expected returns, and interacts with firms' investment rates.

2 The empirical facts

2.1 Data

Capacity utilization. We obtain industry-level utilization data from the FRB's monthly report on Industrial Production and Capacity Utilization (report G.17) that releases publicly available estimates of capacity utilization for a cross-section of industries that cover the manufacturing and mining sectors, as well as utilities. The FRB uses this data to quantify how effectively different industries are utilizing factors of production and to assess inflationary pressures (e.g., Corrado and Mattey (1997)). A major advantage of this FRB data is that it provides a measure of utilization that is available at a much higher frequency than estimates elicited from low-frequency accounting data. The capacity utilization rate ($CU_{i,t}$) of industry i at time t is given by:

$$CU_{i,t} = \frac{IP_{i,t}}{Capacity_{i,t}}. \tag{1}$$

Here, $IP_{i,t}$ is the actual output of the industry, measured by seasonally-adjusted industrial production, and $Capacity_{i,t}$ is the FRB's estimate of the industry's sustainable maximal output at time t. The capacity estimate for most industries is derived from the Quarterly Survey of Plant Capacity Utilization conducted by the U.S. Census Bureau.

Our benchmark cross-section encompasses 45 industries, featuring a mix of durable manufacturers (18 industries), nondurable manufacturers (17 industries), and mining and utilities (10 industries). Due to data availability, the time period of our benchmark analysis ranges from January 1967 to December 2015. The average utilization rate across all industries is roughly 80%. The unconditional moments of the mean, variance and autocorrelation of the utilization rate are similar across different sectors. However, the relative ranking of industries in terms of utilization rates varies substantially over time. We provide further details on the sample composition, including summary statistics, in Section OA.2 of the Online Appendix.

Returns data. Monthly stock return data are taken from CRSP, and accounting data are taken from the CRSP/Compustat Merged Fundamentals Annual file. We obtain returns for portfolios sorted on key characteristics, such as size and book-to-market, as well as asset pricing factors related to the Fama and French (1993, 2015) three- and five-factor models, and the Carhart (1997) four-factor model, from the data library of Kenneth French. Data related to the Hou, Xue, and Zhang (2015) q-factor model are provided by Lu Zhang and firm-level TFP data are from the website of Selale Tuzel.[8] The definitions of the accounting ratios used in this paper are provided in Section OA.1 of the Online Appendix.

2.2 Portfolio formation

To examine the relation between capacity utilization and stock returns in the data, we form portfolios by sorting the cross-section of industries on the basis of each industry's utilization rate. Specifically, at the end of each June from 1967 to 2015 we sort industries into portfolios based on their level of utilization in March of the same year. The three month lag between the release of March utilization data and the June sort date ensures that this strategy is tradeable, as all data used to form portfolios are publicly available by the portfolio formation dates.[9] Each portfolio is then held from July of year t to the end of June of year $t + 1$, at which time all portfolios are rebalanced. Annual rebalancing allows us to capture conditional variation in utilization rates.

We form three portfolios on each June sorting date. The low (high) capacity utilization portfolio includes all industries whose utilization rates are at or below (above) the 10^{th} (90^{th}) percentile of the cross-sectional distribution of utilization rates in March of the same year. The medium utilization portfolio includes the remaining industries with utilization rates

[8]We thank Kenneth French, Lu Zhang, and Selale Tuzel for making this data available to us.

[9]A three month lag between the portfolio formation month and the month in which utilization rates are measured is conservative since the utilization data for month t are released approximately 15 days into month $t + 1$. Since 1967, March utilization rates have been publicly available by April 17th at the latest.

between these breakpoints. We focus on these relatively extreme breakpoints to increase the power of our asset-pricing tests. This is useful because our ability to detect a relation between utilization and future stock returns is already limited by the cross-section of industries for which the FRB reports utilization data. It is worth stressing, however, that since each portfolio contains multiple industries, each of which is comprised of many firms, this choice of breakpoints produces three well-diversified portfolios. We discuss the composition of the portfolios and their characteristics in Section 2.5.[10]

2.3 Fact I: Utilization portfolios and expected returns

Table 1 reports the annual value- and equal-weighted returns of portfolios sorted on capacity utilization using the procedure described above. We document an economically and statistically significant spread between returns of the low and high utilization portfolios. We define the *Utilization Premium* as the average return differential between the low and high utilization portfolios. The table also shows that portfolio returns are monotonically decreasing in the average rate of capacity utilization.

Specifically, the portfolio of industries that utilize a low amount of their productive capacity earns a value-weighted (equal-weighted) average return of 13.64% (10.62%) per annum, whereas the portfolio of industries that utilize a large degree of their capacity earns a value-weighted (equal-weighted) average return of return of 7.96% (5.18%) per annum. The value- and equal-weighted spreads between the returns of the extreme utilization portfolios are 5.67% and 5.44% per annum, respectively. Each spread is significant at the 5% level.[11]

In Section OA.3.5 of the Online Appendix we show that the utilization spread is robust to numerous methodological variations to the portfolio formation procedure. For instance, Table OA.3.10 shows that assigning industries to quintile, rather than decile, portfolios results in a value-weighted capacity utilization spread that is close to 5% per annum and

[10]Table OA.3.13 in the Online Appendix reports the portfolio transition matrix. The matrix show that the probability of transitions out of the extreme portfolios are relatively frequent (about 25%). This demonstrates the importance of the conditional portfolio rebalancing procedure, and the fact that industries change in their relative utilization ranking over time.

[11]The Sharpe ratio of the value-weighted (equal-weighted) spread is 0.32 (0.35). This is comparable to the Sharpe ratio earned by investing in the value premium over the same period.

statistically significant at the 5% level. In addition, Table OA.3.11 shows that the magnitude of the utilization premium rises to over 9% p.a. in the most recent half of the sample period.

Importantly, while the baseline utilization premium is based on industry-level data, we emphasize that the premium is *not* driven by ex-ante sectoral heterogeneity. For example, using the growth rate of utilization as a sorting measure eliminates industry fixed effects in utilization's level, and still yields a sizable utilization-growth spread. We present rigorous evidence in Section 2.7 to show that the utilization premium exists *within* economic sectors.

2.4 Fact II: Utilization portfolios and productivity exposures

We check whether the monotonic pattern between utilization rates and expected return is a result of differential exposures to fundamental macroeconomic risk, as captured by aggregate productivity betas.[12] We consider the following projection:

$$Ret^e_{i,t} = \beta_{0,i} + \beta_{1,i}\text{Agg-Prod}_t + \varepsilon_{i,t}, \tag{2}$$

where $Ret^e_{i,t}$ is the value-weighted excess return of the portfolio of interest, Agg-Prod_t is a proxy for aggregate productivity, and $\beta_{1,i}$ captures the exposure of portfolio i to aggregate productivity. To implement this analysis we consider three different proxies for aggregate productivity: the market return, utilization-adjusted TFP growth from Fernald (2012), and labor productivity from the Bureau of Labor Statistics (BLS). As the latter two proxies are only available quarterly, we aggregate monthly returns to the quarterly frequency when estimating equation (2). Note that when aggregate productivity is proxied via excess market returns, β_0 corresponds to the CAPM alpha.

Table 2 reports the results. The exposure to aggregate productivity falls (almost) monotonically from the low to the high utilization portfolio, regardless of the productivity proxy. Importantly, differences in the productivity betas of the extreme utilization portfolios are not only positive, but are also statistically significant at roughly the 5% level or better. For instance, when measuring aggregate productivity using excess market returns, the difference

[12] The studies of Zhang (2005), Belo and Lin (2012), and Imrohoroglu and Tuzel (2014), among others, also suggest that heterogeneity in exposures to aggregate productivity can explain production-related spreads, such as the value and investment premia. Kogan, Li, and Zhang (2019) also provide a production-based explanation for the investment and profitability premia.

in productivity betas is statistically significant at better than the 1% level.

The table also shows that the intercepts from projecting the utilization spread on each productivity proxy are insignificant at the 5% level, but remain significant at the 10% level in two cases. This raises the question whether the utilization premium can be explained by a single-factor model. For instance, a marginally significant intercept may arise due to non-linear exposures to aggregate productivity, rather than an unaccounted risk factor.

We explore this possibility in Online Appendix Section OA.3.1. We augment projection (2) with a quadratic term of aggregate productivity. This specification allows the relation between portfolio returns and productivity to feature non-linearity (as in the case of time-varying risk exposures). We combine the slope coefficient on the linear and quadratic terms of productivity to construct portfolios' total risk exposure. The results, given in Table OA.3.4, show that when non-linearity is accounted for, aggregate productivity exposures can fully reconcile the utilization premium. Specifically, the utilization premium's total exposure to aggregate productivity increases in both economic magnitude and statistical significance. Likewise, the CAPM alpha of the utilization premium drops from 4.28% per annum (t-statistic of 1.78) under the linear case presented in Table 2, to an insignificant value of 1.28% per annum (t-statistic of 0.41) under the non-linear case presented in Table OA.3.4. Motivated by this evidence, our theoretical model in Section 3 features only a single source of risk: aggregate productivity.

2.5 Capacity utilization portfolios: Characteristics

Portfolio constituents. Panel A of Table 3 reports the average number of firms and industries that constitute each utilization portfolio. By construction, the high and low utilization portfolios each contain approximately 10% of the 45 industries in our sample. Although the number of industries falling into these extreme portfolios is small, these industries are comprised of roughly 960 firms. This means that the low and high utilization portfolios collectively contain about 18% of all firms in our merged CRSP-Compustat sample, and the extreme portfolios are well diversified. Panel A also shows that the average utilization rate is, by construction, monotonically increasing from the low to the high utilization portfolio.

To shed light on the industries underlying each portfolio, Table 4 reports the five industries that populate the extreme utilization portfolios most often. For each industry, the table also reports the sector to which the industry belongs, and the proportion of years the industry is sorted into the portfolio. The key takeaway from this table is that there is a large degree of sectoral variation associated with the industries that populate these portfolios. Panel A shows that leather producers, aerospace manufacturers, and industries that provide supporting services to miners frequently reside in the low utilization portfolio. Panel B shows that the high utilization portfolio often contains mining industries, utilities, and nondurable manufactures.[13] These results provide suggestive evidence that the utilization premium is not driven by any one sector in particular. Section 2.7.1 provides more rigorous evidence that the utilization spread is mostly a within-sector, rather than a cross-sector phenomenon.

Portfolio characteristics. Panel B of Table 3 reports the average industry-level characteristics of each capacity utilization portfolio. There is no statistically significant difference between the low and high portfolios in terms of size, probability, as measured by either ROA or gross profitability. Moreover, there are no differences in asset growth or inventory growth rates between the low and high portfolios. Consistent with the fact that TFP and the hiring rate are positively correlated with capacity utilization (see Table OA.2.3 of the Online Appendix), the low portfolio has both lower industry-level TFP and hiring rates than the high portfolio. However, these differences are small and statistically insignificant. Furthermore, neither external financing frictions, as measured by leverage, debt growth, and equity issuance rates (e.g., Belo et al. (2018)), nor intangible capital, as measured by R&D/ME (e.g., Lin (2012)), differ significantly between low and high utilization firms. The only three characteristics that are significantly different between the two extreme portfolios are the book-to-market ratios, investment rates, and idiosyncratic return volatilities (IVOL).

The latter difference in IVOL cannot account for the capacity utilization premium, as Ang, Hodrick, Xing, and Zhang (2006) show that high IVOL firms earn low expected returns, but low utilization firms have higher IVOL. However, the former differences raise a concerns

[13] While oil extraction appears quite frequently in the high utilization portfolio, we demonstrate in Table 6 and Section 2.7.1 that the utilization premium is positive and significant with the exclusion of the entire mining sector.

that since low (high) capacity utilization industries also tend to be value (growth) industries with low (high) investment rates, the utilization spread may be driven by the value or the investment premium. Each of these potentially confounding effects are well-established in the context of the asset pricing literature. For instance, Fama and French (1993) demonstrate the ability of book-to-market to predict future stock returns, while Titman, Wei, and Xie (2004) show that low investment rates are associated with high future returns.

To establish a degree of independence between the utilization spread and the value and investment premia, the next section conducts a Fama and MacBeth (1973) analysis. We show that the relation between utilization and risk premia remains negative, economically large, and statistically significant after controlling for book-to-market, investment, and a host of other production-based characteristics. Section OA.3 of the Online Appendix provides a double sort analysis that corroborates the results of these regressions.

2.6 Fama-Macbeth and double-sort analyses

Firm-level regressions. We perform firm-level Fama and MacBeth (1973) regressions and show that capacity utilization has predictive power for risk premia that is incremental to the effects of value, investment, and multiple other investment-related characteristics. Given the evidence of Section 2.4, the goal of these regressions is not to propose that the utilization premium represents a new source of risk which is separate from aggregate productivity. Rather, these regressions show that the relation between utilization and risk premia is distinct from known relations between other production-based characteristics and returns, because utilization can vary separately of these characteristics, and affect firms' risk exposures.[14]

These regressions are implemented as follows. In each year t we run a cross-sectional regression in which the dependent variable is a firm's annual excess return from July in year

[14] Another way to show the distinction of the utilization premium from existing production-based spreads is presented in Table OA.3.14 of the Online Appendix. We check whether the utilization spread is absorbed by common unconditional factor models (e.g., the Fama and French (2015) and the Hou et al. (2015) factor models). The annualized alpha resulting from each model is positive. This evidence supports the conclusion of the Fama-Macbeth regressions: the utilization spread contains variation that is largely orthogonal from variation in factor-mimicking portfolios based on investment characteristics (e.g., book-to-market ratios, investment, and profitability). As formerly discussed in Section 2.4, these results are expected since all factors are noisy proxies of the true underlying aggregate productivity, and that utilization-sorted portfolios' exposures to the aggregate productivity are time varying (i.e., non-linear relation).

t to June in year $t+1$, and the independent variables are a vector of the firm's characteristics, $\boldsymbol{X}_t$, measured at the end of June in year t. The cross-sectional regression specification is:

$$R_{i,t\to t+1} = \beta_{0,t} + \boldsymbol{\beta}_t' \boldsymbol{X}_{i,t} + \varepsilon_{i,t\to t+1} \quad \forall t \in \{1967, \ldots, 2014\}. \tag{3}$$

The characteristics we consider are capacity utilization, TFP, hiring, investment over physical capital, capacity overhang, organization capital (as measured by Eisfeldt and Papanikolaou (2013)), the natural logarithms of size and book-to-market, and the lagged annual return. A utilization rate is assigned to each firm following the procedure described in Section OA.3.2 of the Online Appendix, and each control variable is divided by its unconditional standard deviation to aid comparisons between regressions. After running these cross-sectional regressions we compute the time-series average of each estimated slope coefficient to assess the relation between a given characteristic and future stock returns, while holding all other characteristics constant. The results are reported in Table 5.

Columns 1 to 9 of Table 5 include each characteristic in a univariate regression. The average loading of utilization is negative and statistically significant at the 5% level. The loadings on TFP, hiring and investment rates, capacity overhang, and size are also negative and significant, while the loading on book-to-market and organizational capital-to-assets is positive and significant. The relation between lagged annual returns and future returns is statistically insignificant, indicating that returns at the annual horizon have low autocorrelation. The signs of these variables are consistent with the documented spreads associated with each characteristic of interest.[15]

Columns 10 to 16 show that the coefficient on utilization remains negative and significant at the 5% level when we include one or more investment-related characteristics in the regressions. Furthermore, each of the companion characteristics we consider also remains negative and significant. This provides additional evidence that the relation between utilization and stock returns is somewhat orthogonal to the known relations between returns and each of

[15] Imrohoroglu and Tuzel (2014) show that low TFP predicts high stock returns, Belo et al. (2014) find low hiring is associated with high stock returns, Titman et al. (2004) documents the relation between low investment rates and high stock returns, Aretz and Pope (2018) find higher capacity overhang predicts lower stock returns, and Fama and French (1993) discuss how both low market capitalization and high market-to-book ratios predict high stock returns. Additionally, Eisfeldt and Papanikolaou (2013) discuss how higher organizational capital usage predicts higher risk premia. While the estimates associated with lagged returns are not statistically significant, the sign of these point estimates is in line with De Bondt and Thaler (1985).

TFP, hiring, investment, and capacity overhang.

Finally, in Column 17 we augment the regressors of Column 16 with organizational capital, size, book-to-market, and past returns, and consider a regression featuring all eight characteristics simultaneously. In Column 18 we feature all characteristics as well, and also include sector fixed effects.[16] These fixed effects account for potential sectoral heterogeneity in the relation between utilization and risk premia. In both columns, the loading on utilization remains negative and significant at the 5% level. In particular, the result in Column 18 complements the extensive tests presented next in Section 2.7, in support of the fact that the utilization premium is not driven by cross-sectoral effects. Compared to Column 16, the remaining slope coefficients in Column 17 and 18 are largely similar, with the exception of the loading on TFP, which flips sign from negative to positive. However, this change in sign does not compromise the validity of the TFP spread as a number of the investment-related characteristics included in this specification are relatively highly correlated.

Double sorts. Section OA.3 of the Online Appendix validates this regression analysis by conducting portfolio double sorts. The sorts confirm the distinction between the utilization premium, and the value, investment, and overhang premia. In Section OA.3.4 we decompose firms-level TFP into its components and compare the utilization premium to the productivity premium of Imrohoroglu and Tuzel (2014). We show the productivity premium is driven by two underlying and distinct components: the utilization premium from Section 2.3, and a spread based on time-varying technology and markups. Overall, the utilization premium is distinct from other known production-based spreads.

2.7 Utilization premium: Within-sector and firm-level evidence

Section 2.3 shows the existence of a capacity utilization premium based on cross-sectional data from the FRB. We use this FRB data for our main empirical analysis due to its transparency, coverage, and high frequency. While the FRB is only available at the industry level of aggregation, this section alleviates two potential concerns related to the aggregation level of this data. First, in Section 2.7.1 we show that the utilization spread not only exists *across*

[16] In untabulated results, we show that adding sector fixed effects to the previous 16 columns of Table 5 produces quantitatively similar results to those reported in Table 5.

sectors but also exists *within* sectors. That is, we show the utilization spread is not driven by ex-ante sectoral heterogeneity that is unrelated to utilization rates. Second, in Section 2.7.2 we construct firm-level proxies for utilization rates using Compustat data. We show that the utilization spread also exists at the firm-level, with a magnitude that is close to the industry-level evidence.

2.7.1 Controlling for sectoral effects: Within-sector spread

Table 4 shows that some durable industries are often sorted into the low utilization portfolio, whereas mining industries and utilities often exhibit high capacity utilization rates. The former fact raises the concern that the utilization premium may be a manifestation of the durability spread of Gomes, Kogan, and Yogo (2009). That is, the utilization spread may reflect the know fact that durable manufacturers are riskier than nondurable manufacturers. The latter fact raises the concern that the utilization spread is dominated by one particular sector and may reflect ex-ante heterogeneity between different sectors, as opposed to reflecting a risk premium that exists within sectors. We alleviate both concerns below.

First, only three (two) of the five industries that are most commonly sorted into the low (high) capacity utilization portfolio are durable (nondurable) manufacturers (recall Table 4). Furthermore, the most common industry constituents of the high capacity utilization portfolio are not nondurable manufacturers, as may be expected if the utilization spread were strongly associated with the durability premium.

Second, in the left panel of Table 6 we examine the utilization premium within a subsample of industries that only includes durable manufacturers. Specifically, we sort the cross-section of 18 durable manufacturers into three portfolios based on the level of capacity utilization following our benchmark sorting procedure. The capacity utilization spread *within* this subsample of durable manufacturers amounts to 5.85% per annum, and is statistically significant. This demonstrates that the utilization spread is also a within-sector phenomenon that is materially unrelated to the ex-ante heterogeneous exposures of durable and nondurable manufacturers to aggregate risk.

Third, we examine the magnitude of the capacity utilization spread when we exclude the only sector that heavily populates the high utilization portfolio: mining and utilities. The mining and utilities sector is also unique in that its average level of capacity utilization over the sample period is statistically different from that of all other industries (see Table OA.2.2). The right Panel of Table 6 shows the results of sorting all non-mining industries into three portfolios on the basis of capacity utilization. Excluding mining industries and utilities from the sample does not change our baseline results. The utilization spread remains positive, yielding an average return of about 5.3% annually, and statistically significant at the 5% level.

Fourth, in our benchmark analysis we sort industries into portfolios based on the level of each industry's utilization rate. Here we modify this approach by sorting industries into portfolios based on the year-on-year *growth* rate, instead of the *level*, of utilization. Using the growth rate removes any (potential) differences in the average level of utilization across industries. The portfolio formation procedure follows that in Section 2.2, apart from the use of growth rates. The results are reported in Table 7 and show that the value-weighted (equal-weighted) utilization spread is 4.80% (5.74%) per annum and is significant at the 5% level. Portfolio returns are also monotonically decreasing in the utilization growth rate.

Lastly, we complement the empirical evidence above with a theoretical exercise in Section 4.3. We consider the implications of ex-ante parameter heterogeneity on the model-implied utilization premium. Parameter heterogeneity captures any cross-sectoral differences in depreciation, adjustment costs, or elasticity of depreciation to utilization. We show that such heterogeneities contribute only marginally to the utilization premium.

2.7.2 Firm-level capacity utilization premium

We construct a proxy for the unobservable *firm*-level capacity utilization rate. First, for each industry, we project the utilization rate of industry j at time t ($CU_{j,t}$) on salient industry-level production-related characteristics, contained in the vector $\boldsymbol{X}_{j,t}$. For the dependent variable, $CU_{j,t}$, we use either the raw industry utilization or industry-demeaned utilization rate. The latter approach ensures that the fitted value of this projection is not affected by fixed differences in average utilization rate across industries. The choice of $\boldsymbol{X}_{j,t}$ is motivated by the model in Section 3. We use the logarithms of size and book-to-market, the investment to physical capital ratio, IVOL, and TFP. The regression specification is

$$CU_{j,t} = \beta_{j,0} + \boldsymbol{\beta}_j \boldsymbol{X}_{j,t} + \varepsilon_{j,t} \tag{4}$$

By estimating the projection above separately for each industry, the relation between utilization and the characteristics, as measured by $\hat{\boldsymbol{\beta}}_j$, is specific to industry j.

Second, the proxy for the utilization rate of a firm i that belongs to industry j at time t (denoted $\hat{CU}_{i,j,t}$) is obtained by combining the estimated slope coefficients for industry j, obtained via equation (4), with the observable characteristics of firm i, denoted $\boldsymbol{X}_{i,j,t}$,

$$\hat{CU}_{i,j,t} = \hat{\beta}_{j,0} + \hat{\boldsymbol{\beta}}_j \boldsymbol{X}_{i,j,t}. \tag{5}$$

This procedure allows the utilization proxy to vary between firms in the same industry. We use the proxy for firm-level utilization rate to sort firms into portfolios as per Section 2.2, and report the results in Table 8. The table shows that the firm-level utilization premium is about 5% per annum and statistically significant. Similar results are obtained using both raw or industry-demeaned utilization rates in projection (4). The relation between firm-level utilization and average returns also remains monotonically decreasing in either case.

3 The model

We incorporate flexible capacity utilization into a real business cycle model with real options to quantitatively explain the central facts from Section 2: low utilization firms have (1) higher expected returns, and (2) greater exposures to aggregate productivity.

The economy consists of competitive firms that produce a homogeneous good using capital and labor. Firms face convex adjustment costs when altering their capital. In addition, firms pay a fixed cost to reduce capital. This makes disinvestment a real option. When firms choose to increase utilization, their capital depreciates faster. Firms can freely adjust labor and, per Belo et al. (2014), pay wages according to an exogenous wage function. Risk originates from persistent aggregate productivity shocks. The stochastic discount factor is specified exogenously in the spirit of Berk, Green, and Naik (1999) and Zhang (2005).

3.1 Economic environment

Technology. The economy is populated by a continuum of firms that produce a homogeneous good using capital ($K_{i,t}$) and labor ($L_{i,t}$). All firms are subject to the same aggregate productivity shocks, and each firm is subject to its own idiosyncratic productivity shocks. The production function for firm i is given by:

$$Y_{i,t} = \exp(x_t + z_{i,t})\big(u_{i,t}K_{i,t}\big)^{\theta\alpha_K}\big(L_{i,t}\big)^{\theta\alpha_L}, \tag{6}$$

where $\alpha_K \in (0,1)$ and $\alpha_L \in (0,1)$ control the shares of capital and labor in the production function, respectively, and $\alpha_K+\alpha_L = 1$. The parameter $\theta \in (0,1]$ sets the degree of returns to scale associated with the production function. We denote $X_t \equiv \exp(x_t)$, and $Z_{i,t} \equiv \exp(z_{i,t})$.

The control variable $u_{i,t} > 0$ represents the capacity utilization rate of the firm. This variable controls the intensity with which the firm utilizes its capital. In other words, the presence of $u_{i,t}$ in equation (6) provides firms with the flexibility to scale production in response to productivity shocks, while keeping the capital stock fixed.[17]

Each firm's capital stock evolves over time according to the following law of motion:

$$K_{i,t+1} = \big(1 - \delta(u_{i,t})\big)K_{i,t} + I_{i,t}. \tag{7}$$

Here $I_{i,t}$ represents gross investment and $\delta(u_{i,t})$ is the depreciation rate of the firm's capital stock. The depreciation rate depends on the degree to which capital is utilized at time t, and we assume that $\delta'(u_{i,t}) > 0$. Intuitively, this means that if the firm chooses to employ more machines in production, its capital depreciates at a faster rate.

Productivity. Aggregate productivity is denoted by x_t and evolves over time as a stationary AR(1) process:

$$x_{t+1} = \rho_x x_t + \varepsilon^x_{t+1}, \tag{8}$$

where $\varepsilon^x_{t+1} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_x^2)$. The idiosyncratic productivity process for firm i is denoted by $z_{i,t}$ and also evolves according to a stationary AR(1) process given by:

$$z_{i,t+1} = \bar{z}\,(1 - \rho_z) + \rho_z z_{i,t} + \varepsilon^z_{i,t+1}, \tag{9}$$

[17]This type of production function featuring utilization is similar to those in Basu et al. (2006), Jaimovich and Rebelo (2009), and Garlappi and Song (2017). The fact that utilization scales capital is consistent with the FRB's definition of capacity, which primarily reflects changes in capital rather than labor (e.g., Morin and Stevens (2005)). Note that while utilization in the production function is *explicitly* related to capital, the equilibrium choice of labor will *implicitly* (and endogenously) depend on utilization (see equation (18)).

where $\varepsilon^z_{i,t+1} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_z^2)$. We assume that $\varepsilon^z_{i,t+1}$ and $\varepsilon^z_{j,t+1}$ are uncorrelated for $i \neq j$ and that idiosyncratic shocks are uncorrelated with ε^x_{t+1}. $\bar{z}$ is a scaling parameter.

Depreciation, adjustment costs, and wages. Production is subject to three different costs: variable capital depreciation rates, capital adjustment costs, and wages.

We follow Jaimovich and Rebelo (2009) and Garlappi and Song (2017) and specify a depreciation function that features a constant elasticity of marginal depreciation with respect to capacity utilization as follows:

$$\delta(u_{i,t}) = \delta_k + \delta_u \left[\frac{u_{i,t}^{1+\lambda} - 1}{1+\lambda} \right]. \tag{10}$$

Here, δ_k represents the depreciation rate when $u_{i,t} = 1$ (the model's steady state). δ_u measures the additional cost of capital depreciation as the utilization rate is increased. The parameter λ controls the elasticity of depreciation with respect to utilization and determines how costly it for a firm to alter its utilization rate in response to exogenous shocks. Holding all else constant, larger values of λ make increasing the capacity utilization rate more costly and ensures that firms choose a finite level of utilization. We test the positive relation between utilization and depreciation empirically in Section 5.4. We also consider an extension of our model in which the depreciation rate is subject to exogenous shocks in Section 5.5.

Capital adjustment costs are given by the following function:

$$G_{i,t} \equiv G\left(I_{,t}, K_{i,t}, u_{i,t}\right) = \frac{\phi}{2} \left(\frac{I_{i,t}}{K_{i,t}} - \delta\left(u_{i,t}\right) \right)^2 K_{i,t} + f \mathbf{1}_{\left\{ \left(\frac{I_{i,t}}{K_{i,t}} - \delta(u_{i,t}) \right) < 0 \right\}} K_{i,t}, \tag{11}$$

where $\phi > 0$, $f > 0$, and $\mathbf{1}_{\{.\}}$ is an indicator function equal to one when a firm reduces capacity. The adjustment cost function features two components: the standard neoclassical convex cost governed by ϕ and a fixed cost of disinvestment governed by f. This fixed cost reflects frictions in the secondary market for capital, such as the cost of matching with a counterparty (buyer). We introduce the second term for two reasons. First, structural estimations of adjustment cost functions highlight the existence of non-convex adjustment costs (e.g., Cooper and Haltiwanger (2006)). The fixed cost also makes disinvestment a real option. This component is crucial for a negative relation between investment and uncertainty (e.g., Bloom (2009)).[18] Second, the fixed cost of disinvestment is motivated by the large

[18] Put differently, $f > 0$ is crucial for the production model to match the sign of investment's response to

literature that emphasizes the relatively larger costs associated with reducing capacity rather than expanding capacity, both for investment moments and countercyclical risk premia (e.g., Zhang (2005)).[19] Note that our adjustment cost specification in equation (11) is parsimonious compared to other specifications in the literature (e.g., Cooper and Haltiwanger (2006), Belo and Lin (2012)) as it only features two free parameters: ϕ and f.

Firms face a perfectly elastic supply of labor at a given equilibrium real wage rate as per Belo et al. (2014). We follow Jones and Tuzel (2013) and Imrohoroglu and Tuzel (2014) by assuming that the wage rate is positive and increasing in the level of aggregate productivity. Specifically, the wage rate, W_t, is given by:

$$W_t = \exp(\omega x_t), \tag{12}$$

where $\omega \in (0, 1)$ measures the sensitivity of wages to aggregate productivity.

Stochastic discount factor (SDF). In line with Berk et al. (1999) and Zhang (2005) we do not explicitly model the consumer's problem. Instead, we assume that the pricing kernel of the household is given by:

$$\ln(M_{t+1}) = \ln(\beta) - \gamma_t \varepsilon^x_{t+1} - \frac{1}{2}\gamma_t^2 \sigma_x^2, \text{ where } \ln(\gamma_t) = \gamma_0 + \gamma_1 x_t. \tag{13}$$

Here, $0 < \beta < 1$, $\gamma_0 > 0$, and $\gamma_1 < 0$ are constants. This form of the SDF is consistent with Jones and Tuzel (2013) and is adapted from Zhang (2005). Two key features of this SDF are worth noting. First, the volatility of the SDF is time-varying and driven by γ_t. This volatility increases during economic contractions, and results in a countercyclical price of risk.[20] Second, the $-\frac{1}{2}\gamma_t^2\sigma_x^2$ term in the SDF implies that the risk-free rate is constant and equal to $-\ln(\beta)$ in each period. Thus, γ_0 and γ_1 only affect the market risk premium.

Firm value, risk, and expected returns. Firms are all-equity financed. The

uncertainty shocks. While our model does not exhibit stochastic volatility, we confirm that when $f = 0$, the stochastic mean of investment rises in the model when σ_z increases. This counterfactual (i.e., $\partial i/\partial\sigma_z > 0$) does not happen when $f > 0$ because of the standard real option logic.

[19]Untabulated analyses confirm that our results remain materially unchanged when we add a fixed cost for investing to the adjustment cost function. Specifically, we set $G = \frac{\phi}{2}\left(\frac{I}{K} - \delta(u)\right)^2 K + f^-\mathbf{1}\left\{\left(\frac{I}{K} - \delta(u)\right) < 0\right\}K + f^+\mathbf{1}\left\{\left(\frac{I}{K} - \delta(u)\right) > 0\right\}K$, with $f^- > f^+$. While this alternative function also captures the notion of costly reversibility, it includes an extra degree of freedom: f^+. Our goal is to demonstrate that utilization can produce a close fit to the data without relying on a high-dimensional adjustment cost function. Consequently, we use equation (11) without loss of generality.

[20]An economic mechanism that could lead to a countercyclical price of risk is, for example, time-varying risk aversion as in Campbell and Cochrane (1999).

dividend to the shareholders of firm i in period t is given by:

$$D_{i,t} = Y_{i,t} - I_{i,t} - G_{i,t} - L_{i,t}W_t. \tag{14}$$

In each period, each firm chooses $\{I_{i,t}, L_{i,t}, u_{i,t}\}$ to maximize firm value:

$$V_{i,t} = \max_{\{I_{i,t},L_{i,t},u_{i,t}\}} D_{i,t} + \mathrm{E}_t\left[\sum_{j=1}^{\infty} M_{t,t+j}D_{i,t+j}\right], \tag{15}$$

subject to equations (6) – (14). Here, $M_{t,t+j}$ represents the SDF between times t and $t+j$, and $V_{i,t}$ is the cum-divided value of firm i at time t. Finally, the gross stock return of firm i

$$R^S_{i,t+1} = \frac{V_{i,t+1}}{V_{i,t} - D_{i,t}} \tag{16}$$

Equilibrium. Firms' (i) investment, labor, and utilization policies maximize equation (15) given the SDF, and (ii) valuations satisfy equation (15) given their optimal policies.

3.2 Optimality conditions

Whenever $f > 0$ in equation (11), disinvestment is a costly real option and the function $G(\cdot)$ is not differentiable. This means the model's equilibrium conditions are not admissible in closed form. To develop intuition, we analyze the optimality conditions under the tractable case that $f = 0$. We then explain how the optimality conditions change for $f > 0$.

No fixed disinvestment cost ($f = 0$). Labor, $L_{i,t}$, is set such that the marginal product of labor ($MPL_{i,t}$) equals the wage rate:[21]

$$MPL_{i,t} = W_t. \tag{17}$$

Togther with equation (12) this suggests that:

$$L_{i,t} = \left[X_t^{1-\omega}Z_{i,t}\left(u_{i,t}K_{i,t}\right)^{\theta\alpha_k}\right]^{(1-\theta(1-\alpha_k))^{-1}}. \tag{18}$$

The investment choice, $I_{i,t}$, is determined using the Euler equation

$$1 = \mathrm{E}_t\Big[M_{t,t+1}R^I_{i,t+1}\Big], \tag{19}$$

where $R^I_{i,t+1}$ denotes the returns to investment that can be expressed as

$$R^I_{i,t+1} = \frac{MPK_{i,t+1} + \big(1-\delta(u_{i,t+1})\big)q_{i,t+1} + \frac{\phi}{2}\left[\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2 - \Big(\delta(u_{i,t+1})\Big)^2\right]}{q_{i,t+1}}. \tag{20}$$

[21] In our setup $MPL_{i,t} \equiv \frac{\partial Y_{i,t}}{\partial L_{i,t}} = \theta\alpha_L X_t Z_{i,t}\big(u_{i,t}K_{i,t}\big)^{\theta\alpha_K}\left(L_{i,t}\right)^{\theta\alpha_L-1}$.

Here, $MPK_{i,t+1}$ is the marginal product of capital at time $t+1$,[22] and Tobin's marginal q is

$$q_{i,t} = 1 + \phi\left(\frac{I_{i,t}}{K_{i,t}} - \delta(u_{i,t})\right). \tag{21}$$

Since $q_{i,t}$ measures the present value of an extra unit of installed capital, equation (19) shows the trade-off between the marginal cost and discounted marginal benefit of buying capital.

Using equation (21), the first-order condition for the optimal choice of utilization, $u_{i,t}$, is

$$MPU_{i,t} = \delta'(u_{i,t})K_{i,t}. \tag{22}$$

The left hand side of equation (22) represents the benefit of raising utilization, as captured by the marginal product of utilization, or $MPU_{i,t}$, to boost output.[23] The right hand side of the equation represents the cost of raising utilization. A higher utilization rate increases the capital depreciation rate by $\delta'(u_{i,t})$, and results in extra $\delta_u u_{i,t}^{\lambda} K_{i,t}$ units of capital depreciating. Thus, higher utilization implies more output today, but less capital in the future.

Combined, equations (18) and (22) yield a closed-form expression for optimal utilization

$$u_{i,t} = \left[\delta_u^{-1}\theta\alpha_k X_t^{A_x} Z_{i,t}^{A_z} K_{i,t}^{A_k}\right]^{\left(\frac{1}{\lambda - A_k}\right)}, \tag{23}$$

where $A_x = 1 + (1-\omega)\frac{\theta(1-\alpha_k)}{1-\theta(1-\alpha_k)} > 0$, $A_z = 1 + \frac{\theta(1-\alpha_k)}{1-\theta(1-\alpha_k)} > 0$, and $A_k = \frac{\theta-1}{1-\theta(1-\alpha_k)} < 0$.

Given $\lambda - A_k > 0$ and equation (23), we obtain that $\partial u_{i,t}/\partial Z_{i,t} > 0$, $\partial u_{i,t}/\partial X_t > 0$, and $\partial u_{i,t}/\partial K_{i,t} < 0$. When aggregate or idiosyncratic productivity drops, firms seek to drop utilization because the cost of raising utilization (increased depreciation) outweighs the benefit of raising utilization (increased output). Additionally, and all else equal, utilization and capital are negatively related due to decreasing returns to scale, which makes $MPU_{i,t}$ a concave function of both utilization and capital. Thus, equation (23) implies that low utilization firms are firms with low idiosyncratic productivity and high capital.

Together, equations (19) and (23) imply that firm-level investment and utilization comove positively (i.e., $\rho(\frac{I_{i,t}}{K_{i,t}}, u_{i,t}) > 0$). In particular, when firm-level productivity ($z_{i,t}$) drops, firms want to reduce investment because productivity is persistent, suggesting that next period's productivity is likely lower than its steady-state value. Therefore, $MPK_{i,t+1}$ is also smaller in expectation. Simultaneously, a drop in $z_{i,t}$ lowers utilization as explained above.

[22]In this model $MPK_{i,t+1} \equiv \frac{\partial Y_{i,t+1}}{\partial K_{i,t+1}} = \theta\alpha_K X_{t+1} Z_{i,t+1}\big(u_{i,t+1}K_{i,t+1}\big)^{\theta\alpha_K - 1}\big(L_{i,t+1}\big)^{\theta\alpha_L}$.

[23]This marginal product is represented by $\frac{\partial Y_{i,t}}{\partial u_{i,t}} = \theta\alpha_K\left(u_{i,t}\right)K_{i,t}X_t Z_{i,t}\left(u_{i,t}K_{i,t}\right)^{\theta\alpha_K - 1}\left(L_{i,t}\right)^{\theta\alpha_L} > 0$.

Fixed disinvestment cost ($f > 0$). When disinvestment is a costly real option and a firm's productivity drops, there are two opposite forces on the firm's investment decision. On the one hand, the firm wishes to reduce its capital stock as $MPK_{i,t+1}$ is lower in expectation, similar to the case of $f = 0$. On the other hand, the firm would like to "wait and see" if productivity improves before making a decision to sell its machines. By waiting (through inaction), the firm does not incur the fixed cost $fK_{i,t}$ of disinvestment. The balance between these two forces leads to an investment policy whereby firms disinvest if and only if the drop in productivity is sufficiently large. That is, $\exists Z^*(K_{i,t}, X_t)$ such that if $Z_{i,t} < Z^*$, then $K_{i,t+1} < K_{i,t}$, and otherwise $K_{i,t+1} = K_{i,t}$.[24] In the latter case of keeping the capital stock unaltered, firms set their investment rates to the current depreciation rates, $I_{i,t}/K_{i,t} = \delta(u_{i,t})$.

To illustrate this trade-off, Figure 1 plots the firm's investment policy under our benchmark calibration (to be described in Section 3.3) when both capital and aggregate productivity are at their stochastic steady-state values. The figure focuses on the region in which idiosyncratic productivity is negative to highlight firms' optimal investment rate in the presence of the fixed cost f.[25] The figure shows that with fixed utilization (the case of $\lambda \to \infty$, represented by the dashed black line), all firms that "wait and see" set their investment rates to the common and *constant* rate of δ_k. However, with flexible utilization (represented by the solid blue line), the investment rates of waiting firms fluctuate with productivity and over time because $\delta(u_{i,t})$ depends on the stochastic utilization rate. That is, in the presence of the fixed cost, flexible utilization rate eliminates investment "inaction". Moreover, for any value of λ, firms shed capital for very negative values of idiosyncratic productivity.

Importantly, when productivity drops, firms have an extra incentive to lower utilization beyond the forces that govern equation (23). This is because lower utilization *substitutes* selling capital. By further decreasing utilization in low productivity states, a waiting firm's optimal investment rate of $\delta(u_{i,t})$ drops while maintaining capital, $K_{i,t+1} = K_{i,t}$. This

[24]Note that this investment policy breaks the nearly perfect correlation between investment and utilization as in the case of $f = 0$. Utilization and investment can become substitutes for waiting firms, as we explain below. Thus, $f > 0$ is important for a realistic correlation between $u_{i,t}$ and $I_{i,t}/K_{i,t}$.

[25]We provide the same plot for a wider range of idiosyncratic productivity in Figure OA.4.2 of the Online Appendix. As expected, the figure in the Online Appendix shows that the fixed cost affects the investment policy only when idiosyncratic productivity is negative.

increases dividends in bad states. These model features yield important implications for both risk premia (as we explain in Section 4.1), and real quantities such as investment's dispersion (as we explain in Section 5).

3.3 Calibration and solution method

The model is calibrated and solved at the annual frequency, and is specified at the firm level. Consistent with this aggregation level, none of the calibration parameters target industry-level quantities. All targeted moments are either firm- or aggregate-level (i.e., an aggregation of firms across all industries) quantities. We solve the model numerically using value function iteration method, as described in Section OA.5 of the Online Appendix. When simulating the model, we construct model-implied industries by simulating a group of individual firms whose productivities are positively correlated, consistent with the data. We elaborate more on this simulation procedure in Section 4.1. We also consider the potential implications of industry-level heterogeneity on the model's parameters in Section 4.3.

Table 9 presents the set of parameter values used in the model's solution. The first set of parameters governs the dynamics of the exogenous shocks that firms face and also controls the SDF. The second set of parameters controls the production of firms.

Stochastic processes and SDF. We base our annualized values of ρ_x and σ_x, the parameters governing the aggregate productivity process, on the quarterly estimates of these parameters reported by King and Rebelo (1999). We fix ρ_x at 0.922 and σ_x at 0.014. This produces a volatility (autocorrelation) of aggregate sales growth rate of 7.6% per annum (0.41) in the model, closely matching the empirical counterpart of 6.6% per annum (0.46).[26] We set ρ_z to 0.60 and σ_z to 0.30 to match the unconditional volatility of firm-level productivity reported by Imrohoroglu and Tuzel (2014). The long-run average level of idiosyncratic productivity ($\bar{z}$) is a scaling variable set so that the long-run amount of firm-level capital in the economy is one. This implies that $\bar{z} = -0.163$.

[26] Furthermore, the parameters σ_x and ρ_x imply that the volatility of (utilization-adjusted) aggregate TFP growth is 1.43% per annum in the model. This is remarkably close to the volatility of utilization-adjusted TFP measure of Fernald (2012), which is 1.48% per annum. In contrast, the volatility of the non-utilization-adjusted TFP measure in the data is quite larger, at 1.79% per annum. Finally, Table OA.4.16 of the Online Appendix shows that our key results are materially insensitive to perturbing in ρ_x and σ_x.

We choose β, γ_0, and γ_1, the parameters governing the SDF, by matching the average annual real risk-free rate, and the average annual volatility and excess returns of the value-weighted market portfolio, respectively. We set the discount factor, β, to 0.988 to produce an average real risk-free rate of 1.2% per annum. γ_0 and γ_1 are set to 3.375 and -8.8, respectively. These parameter result in a value-weighted equity premium of 5.39% per annum and a market return volatility of 20.89% per annum.

Technology. We fix α_K and α_L at 1/3 and 2/3, respectively. We set θ, the parameter governing the degree of returns to scale in the production function, to 0.95 since slightly decreasing returns to scale are important to keep firm size bounded. δ_k, the average capital depreciation rate, is set to 8% per annum and δ_u, the incremental depreciation rate, is chosen such that utilization is equal to one in the model's deterministic steady state. λ, the parameter governing the elasticity of depreciation to utilization, is chosen to match the volatility of the *aggregate* utilization rate. Setting λ to 3 produces an average annual volatility of aggregate utilization of 4.15% (4.09%) per annum in the model (data). We set ω, the wage sensitivity to aggregate productivity, to 0.20. This value is comparable to both Jones and Tuzel (2013) and Imrohoroglu and Tuzel (2014), and is consistent with the empirical correlation between real GDP growth and wage growth.

We calibrate ϕ, the degree of convex capital adjustment costs, to match the volatility of investment in the data. Setting this parameter to 1.5 results in a model-implied annual volatility of investment of 0.14. This is identical to the empirical volatility of firm-level investment during our sample period. Finally, we set f, the parameter governing the fixed cost of disinvestment and its lumpiness, to 0.028 to match the first-order autocorrelation of firm-level investment. The value of this correlation is 0.58 (0.52) in the model (data).

3.4 Investment and return moments: model versus data

Table 10 compares the fit of the model to the data along dimensions related to distribution of firm-level investment rates, the aggregate utilization rate, and asset-pricing quantities. The main takeaway from this table is that our benchmark model simultaneously produces a realistic distribution of firm-level investment rates and sizable risk premia. Below, we illustrate our model's fit to the data along each dimension.[27]

Time-series of investment rates. Panel A of Table 10 shows that the model-implied volatility and first-order autocorrelation of firm-level investment rates are 14% and 0.58, respectively. These figures are very close to their empirical counterparts since the two capital adjustment cost parameters are set to fit these moments. Additionally, the model also produces realistic estimates for two untargeted moments: the time-series skewness of investment rates (0.66 in the model versus 0.67 in the data) and the second-order autocorrelation of investment (0.38 in the model versus 0.26 in the data).

Cross-section of investment rates. Our model produces a realistic cross-sectional distribution of investment rates *without* targeting any dispersion-related moments of investment. Panel A of Table 10 shows the dispersion of investment rates is 0.11 in the model versus 0.16 in the data. Similarly, the inter-decile range of investment is 0.22 (0.32) in the model (data). We also document that our model produces a positively skewed firm-level investment rate of 1.19 in the model, consistent with the value of 1.89 in the data.

Aggregate capacity utilization rate. Panel A of Table 10 shows the volatility of the aggregate utilization rate is just over 4% in both the model and the data. This close fit is achieved by calibrating λ match this volatility. The model also produces a realistic, and fairly persistent, autocorrelation of utilization (0.7 in the data versus 0.9 in the model).

Aggregate asset-pricing moments. Panel B of Table 10 indicates the model-implied annual risk-free rate and equity premium are 1.2% and 5.4%, respectively. The volatility of excess market returns in the model is 20.9%. These three moments are calibrated to match the data. The model also produces a slightly negative autocorrelation of excess market returns that is close to its empirical counterpart of -0.05. Here, model-implied returns are multiplied by 5/3 to account for financial leverage.

Cross-sectional risk premia. Panel B of Table 10 also demonstrates that our model is quantitatively reliable regarding cross-sectional risk premia. This is shown by the fact that the model produces book-to-market and investment spreads that align with the data. The value premium in the model is 3.76% per annum, whereas this spread is 3.71% per annum

[27]Section 2.1 provides details about the data used to construct the empirical estimates for the table.

in the data. The model-implied investment premium of 4.27% per annum is also close to its empirical magnitude of 3.7% per annum. The success of the model along this dimension is achieved without calibrating any model parameters to match either of these spreads.

4 The utilization premium: theorical evidence

4.1 Model-implied capacity utilization spread

Simulation. The empirical section documents a utilization premium using both industry-level (recall Section 2.3) and firm-level (recall Section 2.7.2) evidence. Consequently, we assess the model's ability to produce a monotonically decreasing relation between capacity utilization rates and portfolio returns at both levels of aggregation.

For the model-implied firm-level analysis we simulate a cross-section of four thousand firms. We then sort this cross-section of firms into portfolios on the basis of realized capacity utilization rates. Specifically, at each point in time t, the low (high) capacity utilization portfolio includes all firms whose utilization rates were at or below (above) the 10^{th} (90^{th}) percentile of the cross-sectional distribution of utilization rates at time $t-1$. This procedure is consistent with our empirical portfolio formation procedure described in Section 2.2.

For the model-implied industry-level analysis, we construct simulated industries by aggregating groups of simulated firms. Although the model does not feature an industry-specific productivity shock, we capture the fact that firms in a given industry share a common productivity component by correlating the firm-level productivities of all firms within an industry. Specifically, when simulating a group of M individual firms that comprise an industry, we set the correlation between each pair of firms' ε^z shocks to 0.50. This choice of correlation coefficient is consistent with the fact that in the data, the average time-series correlation between the annual return of a given firm and the return of its industry is 0.46.[28] To parallel the number of industries and firms per industry to the data (see Panel A of Table 3), each model-implied industry represents a value-weighted aggregate of 100 firms, and the

[28]The industry-level results are materially unchanged when we perturb the correlation between the shocks ε^z of firms in the same industry. Untabulated results show that the model-implied industry-level utilization spread falls within the empirical confidence interval when the correlation is halved (increased) to 0.25 (0.75).

economy is comprised of 50 simulated industries.

For each industry, the utilization rate is computed as the value weighted average of the firm-level utilization rates across all industry constituents. We sort the cross-section of simulated industries into capacity utilization portfolios in an identical fashion to the empirical exercise and to the firm-level model simulations, as previously described.

For both the firm-level an industry-level analyses we compute both population and finite-sample moments. The population moments are based on a simulation of the economy over 40,000 periods. The model-implied finite-sample distribution is obtained from 500 simulations of the economy over 50 periods. The number of periods of the short-sample analysis corresponds to the empirical sample length from 1967 to 2015.

Expected returns. Table 11 shows the average firm-level returns (Panel A) and industry-level returns (Panel B) associated with the utilization-sorted portfolios, and the respective capacity utilization spreads in our simulated economy.

Panel A of Table 11 corresponds to the firm-level capacity utilization spread reported in Table 8. Consistent with the data, the model-implied relation between utilization and average stock returns is negative and monotonic. Low utilization firms earn a larger risk premium. On the basis of finite-samples, low (high) utilization firms in the model earn an average return of 9.86% (4.64%) per annum. The model-implied firm-level utilization premium is about 5.2% per annum, and is almost identical to the empirical firm-level spread reported in Table 8. We obtain almost identical figures via population moments.

Panel B of Table 11 corresponds to the (value-weighted) industry-level capacity utilization spread reported in Table 1. The relation between utilization rates and average returns remains monotonic and negative at the industry-level. The median industry-level utilization premium across the finite-sample simulations of our economy is 4.04% per annum, with a 95% confidence interval ranging from 0.38% to 8.75% p.a. The empirical industry-level utilization spread of 5.6% per annum falls within the model-implied confidence interval. The same holds for each individual portfolio: the mean empirical returns for the low, medium, and high portfolios all overlap within the respective model-implied confidence intervals.

Risk exposures. Table 11 also reports the exposure of each utilization portfolio to the model-implied aggregate excess market return. The table also shows the spread between these exposures. Specifically, the exposures reported in Panel B correspond to the empirical ones shown in the left-most columns of Table 2. In the model, the market return is an observable proxy for aggregate productivity, as the model features only one aggregate shock.

In line with our second empirical fact, the model-implied exposure of each portfolio to the market (aggregate productivity) decreases with the portfolio's utilization rate. The spread in betas between the low and high utilization portfolios is 0.17 (0.26) in the model (data). Comparing Panels A and B of Table 11 shows that aggregation hardly alters the magnitudes of the risk exposures, which are similar using firm- or industry-level analyses.

Lastly, the empirical evidence in Section 2.4 shows that the CAPM alpha of the utilization premium is sizable in the data, at about 4.3% per annum, but statistically insignificant at the 5% level. In Table OA.4.17 of the Online Appendix we show that the model can replicate this result. We mimic the empirical exercise by considering short-sample simulations of our economy, using industry-level returns to construct the utilization spread's alpha. The CAPM can explain the model-implied utilization spread. The mean model-implied CAPM alpha of the spread is 3.2% per annum, but statistically insignificant at the 5% level (consistent with the data).

4.2 Economic rationale for the capacity utilization spread

The mechanism relating capacity utilization to risk premia in the model hinges on three ingredients: (1) a quadratic capital adjustment cost ($\phi > 0$), (2) a fixed cost of disinvestment ($f > 0$), and (3) a countercyclical market price of risk ($\gamma_1 < 0$). Firms in the model are risky because they can neither costlessly (nor fully) adjust their capital stock $K_{i,t}$ in response to productivity shocks. However, flexible utilization rate, $u_{i,t}$, provides firms with a mechanism to reduce these capital frictions. Utilization also directly impacts the cyclicality of firms' output. Consequently, the utilization rate is inherently tied a firm's risk and its expected returns. We illustrate this logic by shutting down ingredients (2) and (3) in our economy, as well as utilization, and explaining the role of each ingredient in turn.

Quadratic adjustment costs only. Assume the only frictions present are quadratic capital adjustment cost, and utilization is fixed ($\lambda \to \infty$). As the returns to scale in our model are almost constant ($\theta \approx 1$), a sufficient statistic for the ex-dividend firm valuation is Tobin's q, which is given in equation (21), with $\delta(u) = \delta_k$ whenever $\lambda \to \infty$. The risk of each firm is determined by the interaction between firm-level investment and capital adjustment costs, as implied by Tobin's q. In other terms, the ex-dividend firm's productivity beta, $\beta_{i,t}$, can be written as $\beta_{i,t} = \frac{\partial V_{i,t}}{\partial \varepsilon_{x,t}} \approx \frac{\partial}{\partial \varepsilon_{x,t}} q_{i,t}(i_{i,t})\dot{K}_i$. As $q'(i_{i,t}) > 0$, the valuation of (disinvesting) investing firms (drops) rises, and thereby covaries more with aggregate productivity in good (bad) states in which x_t is (low) high. Simply put, firms that make large (dis)investments are required to pay large capital adjustments costs which restrict the ability of shocks to be absorbed in investment. As shocks are not fully absorbed in quantities, they are absorbed in installed capital's price. Thus, both high and low investment rate firms are risky depending on the phase of the cycle (i.e., $\beta_{i,t} \uparrow$ if either $i_{i,t} \uparrow$ and $x_t \uparrow$, or $i_{i,t} \downarrow$ and $x_t \downarrow$).

When the capacity utilization rate in the economy becomes variable, the interaction between utilization and investment can mitigate (dis)investment adjustment costs, and hence reduce the risk associated with altering capital. Consider a firm facing lower productivity. As discussed in Section 3.2, while the firm still has the incentive to reduce its capital stock, thereby exposing itself to potentially large quadratic capital adjustment costs, the firm also has the incentive to lower its utilization rate for two reasons. First, equation (22) suggests that by lowering its utilization rate, the firm benefits from a reduction in its depreciation rate. This conserves capital for more productive states in the future (i.e., $u_{i,t} \downarrow \Rightarrow \delta(u_{i,t}) \downarrow \Rightarrow K_{i,t+1} \uparrow$). Second, because lower utilization rate implies lower depreciation (lower natural rate of investment), the firm can pay a lower quadratic adjustment cost to disinvest. To see this, consider equation (11). If $\delta(u_{i,t})$ drops whenever $I_{i,t}/K_{i,t}$ drops, then the gap between the two shrinks, reduing the quadratic cost. Equation (21) implies that this creates a partial hedge for (dis)investment risk in (bad) good times, by attenuating the fluctuations in q.[29]

The incentives above create positive comovement and complementarity between a firm's

[29]In principle, if utilization was extremely, and counterfactually, volatile, then a large drop in $\delta(u_{i,t})$ could dominate the drop in $I_{i,t}/K_{i,t}$, thereby raising $q_{i,t}$ in bad states and making the firm "safe" (i.e., lead to a countercylical valuation). In our benchmark calibration, including all calibrations used for sensitivity analysis, this does not occur in equilibrium.

need to disinvest and low utilization. Therefore, low utilization firms, which have low idiosyncratic productivity and high capital according to equation (23), are riskier during aggregate economic downturns, because they face large capital downscaling costs which they partially hedge by lower utilization (i.e., $\beta_{i,t} \uparrow$ if $u_{i,t} \downarrow$ and $x_t \downarrow$ by $corr(u_{i,t}, i_{i,t}) > 0$). The converse holds for high utilization firms during periods of high aggregate productivity. Hence, both very high and very low utilization firms are risky, depending on the state of the aggregate productivity.[30] We break the risk symmetry between high and low utilization firms by introducing ingredients (2) and (3).

The role of the fixed disinvestment cost for risk. When we enrich the model with ingredient (2), the fixed cost of disinvestment ($f > 0$), we introduce a higher friction to disinvest. Reducing capital becomes a costly real option. As discussed in Section 3.2, firms facing a moderate drop in productivity do not disinvest immediately. They "wait and see" if productivity improves before exercising the costly disinvestment options. While not exercising the real option, the risk of the firms who "wait" rises (their capital is further from optimum with this friction). Simultaneously, these waiting firm substitute exercising the option to sell machines by temporarily lowering utilization (further). This helps to partially hedge capital risk. To see this, note that all waiting firms set their investment rate to the depreciation rate to maintain the capital stock. By lowering utilization firms reduce $\delta(u_{i,t})$, which lowers the required investment rate needed to maintain capital. Lowered investment in bad states raises the current dividend, which creates a partial hedge compared to the case in which utilization is fixed.[31] Since the underlying friction in the market for selling capital are even greater for low utilization firms when $f > 0$, their betas in bad states of the world exceeds the betas of high utilization firms in good states (i.e., $\beta_{U_L,X_L} > \beta_{U_H,X_H}$, where $X_L(X_H)$ is low (high) productivity, and $U_L(U_H)$ is a low (high) utilization firm).

[30] Note that while the ex-dividend productivity beta of low (high) utilization firms is large in bad (good) times – as reflected by q – the cum-dividend productivity beta is even larger for these extreme firms. This is because lower (higher) utilization in times when x_t is low (high) decreases (raises) the current output precisely in bad (good) states, which lowers (raises) payout and increases the cyclicality of payouts. This effect is also important for amplifying cross-sectional spreads in the model, such as the value premium, compared to a model with fixed utilization as we discuss further in Section 5.3.

[31] In other words, when utilization is fixed, firms that wait to sell capital set their investment rate to δ_k. When firms contemporaneously lower utilization, they set their investment rate to $\delta(u_{i,t}) < \delta_k$. As the current dividend and investment are negatively related, the firms payout rises, all else equal.

The role of the countercylical price of risk. The second mechanism that breaks the symmetry is ingredient (3), the countercyclical market price of risk. Since the market price of risk is higher in low aggregate productivity states (i.e., $\gamma_t'(x_t) < 0$), the firms whose returns covary more with economic conditions during bad times command a larger risk premium. As discussed above, low utilization firms are riskier (have higher betas) during economic downturns. Since these states feature a higher market price of risk, low utilization firms earn a risk premium (i.e., if $x_t \downarrow$ and $u_{i,t} \downarrow$, then $E[R^e_{i,t+1}] \approx \beta_{i,t}\gamma(x_t) \uparrow$ because $\beta_{i,t} \uparrow$ and $\gamma(x_t) \uparrow$). In contrast, high utilization firms earn a much lower premium (in both good and bad states). High utilization firms have greater exposures ($\beta_{i,t}$) to aggregate risk only in good times. Since the market price of risk is very small in these periods, the risk premium of high utilization firms is also small. Overall, this logic implies that low utilization firms should earn larger risk premia, consistent with Table 11.

Combined, ingredients (2) and (3) yield a monotonic relation between utilization and risk premia. The real option channel impacts (mostly) firms with moderate idiosyncratic productivity that find it optimal to leave their capital unaltered in bad states. As a result, medium utilization firms are considerably riskier than high utilization firms. The countercylical price of risk impacts (mostly) firms with lower idiosyncratic productivity that have a high beta. As a result, low utilization firms are riskier than both medium or high utilization firms. Moreover, a very low price of risk in good states implies that the risk associated with high utilization firms is not translated into a higher risk premium in good times.

Model extensions, sensitivity analysis, and further discussion. Section 4.3 shows that industry-level heterogeneity in model parameters induces only a small quantitative effect on the utilization premium. In Section 5.5 we consider an extension of the model that introduces an exogenous shock to firms' depreciation rates. Likewise, this additional shock has only a small impact on the model-implied spread. Section OA.4.2 of the Online Appendix illustrates the model's intuition for the spread numerically, by perturbing the model's parameters. We show the spread falls when ϕ, ρ_x, or σ_x drops, when f is zero, and with a constant market price of risk. Section OA.4.3 discusses the model's assumptions in detail. Section OA.4.1 shows that conditioning on book-to-market, the utilization premium remains positive in the model, in line with the data.

4.3 Sectoral heterogeneity and the utilization premium

The benchmark utilization premium is based on industry-level data. As the structural parameters of industries may differ, this can induce dispersion in risk premia that are unrelated to utilization. Here, we design an experiment to put an upper bound on how much these ex-ante differences impact the utilization spread.

Specifically, let x denote a parameter of interest, let x_0 denote the value of x in our benchmark calibration, and let N represent the number of firms in the economy. First, we solve the model twice: once when x is doubled to $x_U = 2x_0$, and once when x is halved to $x_D = 0.5x_0$. Next, we simulate $N/2$ firms implied by the model solved for each x_U and x_D, and combine these two simulations into one economy of N firms. These two simulations aim to capture *extreme* differences between industries in terms of parameter x. Finally, we sort the cross-section of N firms on the basis of utilization in an identical fashion to our baseline model results. The difference between the model-implied utilization premium here, and the utilization premium in our benchmark simulations, quantifies an upper bound on the effect that ex-ante heterogeneity in parameter x has on the utilization premium.

We consider heterogeneity in three parameters: the depreciation rate, δ_k, elasticity of depreciation to utilization, λ, and convex adjustment cost, ϕ. The results are reported in Table 12. In comparison to Panel A of Table 11, heterogeneity in ϕ, λ, and δ_k add up to 0.06%, 0.13%, and 0.87% per annum, respectively, to the premium. Thus, ex-ante sectoral heterogeneity only implies a marginal amplification of the model-implied utilization spread.

5 Utilization's role for macro-finance modeling

The implications of flexible utilization for asset prices span beyond the utilization premium. We highlight the roles of flexible utilization for jointly targeting cross-sectional risk premia and investment moments in the presence of real options. We first show the failures of the model without utilization to target asset-pricing and production moments. We then explain how utilization provides a solution to these misses. We demonstrate that flexible utilization permits us to target key moments with a lower degree of adjustment costs vis-à-vis a model with fixed utilization. Lastly, we show that utilization comoves positively with depreciation, as implied by our model. Accounting for utilization when estimating depreciation can potentially lead to more precision and higher-frequency depreciation dynamics.

5.1 A fixed utilization model: the failures

The benchmark model's success in jointly fitting (i) the volatility and skewness of investment, both across time and across firms, and (ii) risk premia, crucially hinges on variable capacity utilization rates. To illustrate this point, row (1) of Table 13 shows model-implied moments in an economy without flexible utilization (i.e., $\lambda \to \infty$).

With fixed utilization, the distribution of investment rates exhibits far less variability and asymmetry compared to the data both in the time-series and the cross-section. The time-series skewness of firm-level investment turns to -0.09, at odds with its empirical sign and magnitude of 0.67. Investment's time-series volatility drops to only 11%, and its autocorrelation becomes slightly too high. Cross-sectional moments also become severely distorted. The dispersion of investment rates is about a half of its empirical counterpart (7% in the model vs 16% in the data). The cross-sectional skewness of investment rates is merely 0.11 in the model, whereas it is much higher in the data (about 1.9). The model-implied value and investment spreads are also about 1% per annum smaller in this model than the data.

The fixed utilization model fails to capture the aforementioned moments since (1) the fixed adjustment cost makes disinvestment a real option, and (2) without flexible utilization, a firm's *only* way to respond to a negative productivity shock is by exercising this option.

As discussed in Section 3.2, if a drop in productivity at time t is not extremely severe, then a "wait and see" effect tends to dominate. Thus, declines in productivity typically lead to periods of investment-policy inaction in which many firms do not alter their capital stock. Each waiting firm j sets its investment rate, $i_{j,\tau}$, to the constant depreciation rate of δ_k for all $\tau \in [t, t+\hat{t})$, where $\hat{t}$ is the ending time of the endogenous inaction period. Since a mass of waiting firms are clustered around the center of investment's distribution (i.e., around δ_k), investment's dispersion and cross-sectional skewness both decrease.

Furthermore, if productivity remains persistently low, then at time $t+\hat{t}$ waiting firms pass a tipping point in which they are overly burdened with unproductive capital and choose to disinvest this capital sharply. This implies that $i_{j,t+\hat{t}} << \delta_k$.[32] Thus, these periods of inaction are often followed by negative investment spikes, producing the negative skewness of firm-level investment that is inconsistent with the data.[33]

The distorted distribution of investment rates in the model with fixed utilization also has an adverse impact on risk premia. Because investment's distribution features too little dispersion and asymmetry, there is too little heterogeneity between firms' risk exposures. Sorting firms into portfolios based on investment (or valuation ratios) implies that both the top and bottom quintiles (tails) contain fewer extreme outcomes compared to the benchmark with flexible utilization. As differences in cross-sectional risk premia are fundamentally driven by heterogeneity in investment, cross-sectional spreads get smaller with fixed utilization.

While the model misses above are broadly related to the recent debate in the literature on the relevance of costly reversibility (e.g., Bai et al. (2019); Clementi and Palazzo (2019)), it is important to highlight the distinction. The existing debate relates to models *without* real options. In contrast, our model features theoretically and empirically motivated real options to disinvest (e.g., (Bloom, 2009)). Real options distort investment's distribution beyond the convex adjustment costs both Bai et al. (2019) and Clementi and Palazzo (2019) focus on.

5.2 Flexible utilization: a solution

Our benchmark model with flexible utilization overcomes the counterfactuals outlined in Section 5.1 by making the depreciation rate endogenously stochastic. This improved model fit is highlighted in row (2) of Table 13 by showing model-implied moments under the benchmark value of λ. When firms can choose utilization, they have an extra mechanism

[32] Put differently, when firms are close to the disinvestment threshold, then the investment policy is locally concave and the expected value of investment becomes negative.

[33] Importantly, the counterfactuals in the model with fixed utilization cannot be remedied simply via the aggregation level. As many real options operate at the plant level, one can argue that a collection of production units in the model comprise one firm. Aggregation of many units into a single firm does indeed smooth model-implied investment rates by shrinking periods of investment inaction, and lowering the size of disinvestment jumps. However, these model-implied moments remain unaligned with the data. We verify this in untabulated simulation by aggregating 100 production units into a firm. The resulting model-implied volatility of investment is smaller than the data. While the skewness of investment turns positive, this quantity is close to zero (remaining significantly lower than the data).

by which to scale down production in response to adverse productivity shocks, even as they "wait and see" if productivity recovers. That is, firms can respond to moderate drops in productivity by utilizing their existing machines less intensively rather than selling machines. As underutilized capital depreciates slower, more capital is preserved for more productive future periods (i.e., $\delta(u_{j,\tau}) < \delta_k$ if $u_{j,\tau} < 1 \ \forall \tau \in [t, t+\hat{t})$).

Lower utilization reduces the natural investment rate needed to maintain the current capital stock. Thus, even as firms wait to sell capital, the investment required to maintain existing machines, $i_{j,\tau} = \delta(u_{j,\tau})$, becomes endogenously stochastic. This time-varying depreciation eliminates the long periods of constant investment. The time-series volatility of firm-level investment rises, and the cross-sectional dispersion of investment increases. To see the latter, note that firms' utilization rates depend on idiosyncratic productivity shocks. Since these shocks differ between waiting firms, $u_{j,\tau} \neq u_{k,\tau} \Rightarrow i_{j,\tau} \neq i_{k,\tau}$ for firms j and k.

Moreover, the positive correlation between productivity and utilization also implies that firms opt to raise utilization in times of high productivity. Utilizing capital more intensively in good times raises both depreciation and the natural rate of investment (i.e., $\delta(u_{j,\tau}) > \delta_k$), and means that larger investments are needed to expand capacity in future periods. To see this, suppose that at time τ a firm wants to expand capacity by $\delta_k K$. With fixed utilization, the required investment rate is $i_\tau = 2\delta_k$. However, with flexible utilization, the required investment rate rises to $i_\tau = \delta(u_{j,\tau}) + \delta_k > 2\delta_k$. Since investment becomes more procyclical, its time-series and cross-sectional skewness rise and turn positive (in line with the data).

The increases in the skewness and dispersion of investment under flexible utilization also boost risk premia spreads, as seen by comparing the value premium between rows (2) and (1) of Table 13. A larger value premium under flexible utilization can be attributed to the fact that the cross-section of investment rates is more dispersed and almost 12 times as skewed in the model with flexible utilization. Greater dispersion in investment leads to more heterogeneity in risk exposures to aggregate productivity, which increases return spreads.[34]

[34]The increase in the cross-sectional skewness of investment also has an impact on the value premium. With fixed utilization, and *symmetric* cross-sectional distribution, the portfolio of growth firms (bottom 20% of book-to-market) includes both firms with very high and moderately high investment rates (or Tobin's Q). With flexible utilization, and *asymmetric* cross-sectional distribution, the right tail of investment's distribution becomes thicker, and the portfolio of growth firms includes firms with only very high investment

More generally, as shown in rows (3) to (6) of Panel A in Table 13, the value of λ has a substantial quantitative impact on matching the data. As utilization becomes more flexible (i.e., λ decreases), the time-series/cross-sectional skewness and volatility of investment rise, the autocorrelation of investment slightly declines, and risk premia increase as well. This generally moves each moment towards its empirical counterpart when compared to the case of $\lambda \to \infty$. In particular, row (6) shows that when utilization becomes less flexible (i.e., λ is finite but high), investment's skewness and dispersion are too low. Rows (4) and (5) show that our results are only mildly affected by small perturbations of the benchmark value of λ. However, utilization cannot be overly flexible. When λ is very low, as in row (3), the volatility of utilization exceeds the 95% confidence interval of this quantity in the data.

5.3 Required adjustment costs under flexible utilization

Without flexible utilization, the problem of matching investment's moments with the data is not simply alleviated by recalibrating the model. In this section we show that flexible utilization can reduce the magnitude of exogenous adjustment cost parameters required to target investment and risk premia jointly. We illustrate this role of utilization by perturbing the capital adjustment cost parameter in a model without utilization.

Specifically, in rows (7) to (10) of Panel B in Table 13 we alter the quadratic adjustment cost while keeping utilization fixed. Rows (7) and (8) consider the case of lower frictions compared to the benchmark. Sufficiently lower friction (row (7)) can help turn the time-series skewness of investment to a positive value, but the cross-sectional skewness of investment is still too small. Lower frictions also cause risk premia to fall. The value premium, which is already too low in the model with fixed utilization, falls in row (7) to almost half of its empirical magnitude.

The diminished value premium in the model with fixed utilization can be boosted by increasing the quadratic capital adjustment cost. With higher adjustment costs, shocks are absorbed in asset prices rather than investment quantities. We demonstrate this in rows

rates. As these firms expand capacity significantly (suggesting a much higher Q) precisely when the price of risk is high (bad states), their skewed investment behavior provides an excellent hedge against bad states. This decreases the risk premium of the growth portfolio, and increases the magnitude of the value premium.

(9) and (10). We search for an adjustment cost parameter ϕ to match the value premium in the model with fixed utilization. Our structural search suggests that ϕ needs to be around 3.00 to match this spread (see row (10)). While this parameter is broadly consistent with existing literature, this value is *double* the value of ϕ under our benchmark model with flexible utilization. Moreover, doubling ϕ simultaneously distorts the distribution of investment rates. Investment's dispersion becomes a quarter of its empirical magnitude. The time-series skewness of investment becomes even more counterfactually negative.[35]

Flexible utilization provides a channel that addresses the aforementioned concerns. Row (2) of Table 13 shows that flexible utilization allows our baseline model to feature adjustment costs that are smaller than those required with fixed utilization. These smaller costs are sufficient to simultaneously produce sizable risk premia spreads, including many periods of depressed investment.[36] This happens because of the following key mechanisms.

The first mechanism is related to the impact of lower utilization on observed investment rates. For a given quadratic adjustment cost parameter, flexible utilization implies more observed disinvestment while keeping the amount of friction (risk) the same. To see this, suppose a firm wishes to drop its capital stock by $\delta_k K$. With fixed utilization, the firm chooses an investment rate of $i = 0$, and the quadratic cost is proportional to δ_k^2. However, with flexible utilization, a drop in productivity triggers a drop in utilization, which in turn lowers the firm's depreciation to $\delta(u_{i,t}) < \delta_k$. To shed $\delta_k K$ capital, the investment rate is set

[35] In untabulated results, we further verify that under fixed utilization, the value premium cannot be targeted successfully in the model (jointly with investment's moments) by changing the fixed cost f. Specifically, we find that lowering the fixed cost f causes investment's skewness to rise and move closer to the data. However, even in the extreme case of $f = 0$, the cross-sectional skewness of investment is only a half of its empirical magnitude. Moreover, lowering f decreases the magnitude of the value premium (e.g., when $f = 0.01$, the implied value premium is merely 2.7%). Similarly, we find that while raising the fixed cost f to 0.06 allows us to obtain a value premium of 3.2% (roughly consistent with the data), this causes the model's investment mismatch to become even more severe. The time-series and cross-sectional skewness of investment become counterfactually negative (about -0.75), and investment's volatility falls to 10%.

[36] Moreover, when utilization is flexible, this result is not very sensitive to small perturbations of ϕ. Rows (12) and (13) of Table 13 show that when the quadratic adjustment cost (ϕ) slightly increases (decreases), the volatility of investment drops (rises), the value premium slightly increases (decreases), but these moments are almost identical to the benchmark in row (2). Row (14) shows that if ϕ is set to 3.00 (which is required in the case of fixed utilization), then the implied value premium is almost 5%, about 1.5% above its value under fixed utilization. In this case, the cross-sectional skewness of investment aligns very well with the data, but the cross-sectional dispersion is too low.

to the lower rate of $i = -\delta_k + \delta(u_{i,t}) < 0$. The quadratic cost will be unaltered, and remain proportional to $(-\delta_k + \delta(u_{i,t}) - \delta(u_{i,t}))^2 = \delta_k^2$. Thus, in a model with flexible utilization, one may see more disinvestment without compromising on the frictions that induce risk premia.

The second mechanism involves the changes in the cross-sectional distribution of investment rates that are caused by flexible utilization. As we outline in Section 5.2, utilization makes the cross-sectional distribution of investment more dispered and skewed. By featuring more extreme observations in the tails of investment's distribution, one can obtain quantitatively large return spreads with moderated values of adjustment costs.

The third mechanism is utilization's ability to enhance payout cyclicality. Value firms have low idiosyncratic productivity and high capital, and desire to reduce excess capital in bad states. With fixed utilization, these firms are riskier because they need to pay large quadratic costs that reduce their payoff precisely when aggregate productivity is low. With flexible utilization, these firms also desire to lower utilization to conserve capital for future periods. The reduction in utilization implies today's output is even lower, contemporaneously with a bad aggregate state. Thus, the cyclicality of output is larger, amplifying risk.[37]

5.4 Utilization and depreciation dynamics

Equation (10) suggests that firms' depreciation rates should correlate positively with their utilization rates. In this section we check this prediction and explore its implications for the accuracy and the frequency of depreciation's measurement.

We examine the relation between utilization and depreciation via the projection

$$\Delta\delta_{j,t} = d_j + d_u \Delta u_{j,t} + d_x X_{j,t} + \varepsilon_{j,t},$$

where j denotes an industry index, $\Delta\delta_{j,t}$ is the log growth of industry j's depreciation rate from BEA, $\Delta u_{j,t}$ is the log growth of industry j's utilization rate, and $X_{j,t}$ is a control

[37]To conclude the section, we note that the model with fixed utilization can potentially match the value premium using a more elaborate adjustment cost function. For example, extra adjustment costs may include piecewise quadratic and linear terms (e.g., Bloom (2009) and Belo and Lin (2012)). However, these additional costs require more exogenous calibration parameters. Furthermore, while featuring a higher degree of frictions may help target risk premia, these same frictions may further inhibit dispersion-related moments of investment. By contrast, capacity utilization relies on only one additional parameter, the elasticity of depreciation to changes in utilization, that is calibrated to the volatility of aggregate utilization rather than an investment-related moment.

variable. We use the log growth of depreciation and utilization to reduce persistence in these variables, and to account for a non-linear relation between the level of the two. All variables are standardized for the ease of interpretation. The results of the projection are reported in Table 14. In columns (1) and (2) of the table we run the projection without any controls. We show that the simple correlation between log depreciation growth and log utilization growth is 30%, and that this correlation is not affected by the inclusion of industry fixed effects.

Recent studies in production-based asset pricing show that BEA- and Compustat-implied depreciation rates are strikingly different. The use of one over the other can lead to economically sizable differences in the distribution of gross investment rates (e.g., Clementi and Palazzo (2019); Bai et al. (2019)). In line with these papers, columns (3) and (4) of Table 14 demonstrate the discrepancy between these two depreciation measures. We set $X_{j,t}$ to be the log growth of industry j's Compustat-based depreciation rate, and restrict d_u to zero. The correlation between the growth of these depreciation measures is only 3%.[38]

In columns (5) and (6) we do not restrict d_u to be zero. First, the positive correlation between BEA-implied depreciation growth and utilization growth remains positive and sizable when controlling for Compustat-implied depreciation. Second, the (partial) correlation between the growth rates of BEA- and Compustat-implied depreciation increases to 14%. Thus, utilization narrows the wedge between these two measures. While measurement error may exist in both measures, the fact that the correlation between the two increases when controlling for utilization suggests that utilization can be used to accurately filter the true depreciation rate. We briefly demonstrate this point by proposing a theoretically-motivated method to measure the *aggregate* depreciation rate based on utilization data, but leave the full exploration of this filtration problem to future research.

As utilization data is available at the monthly frequency, the utilization-implied depreciation rate we propose is computed at a higher frequency than depreciation rates implied by either BEA or Compustat. First, to be consistent with the model, we adjust each industry's utilization rate to have a mean of one. Then, for each industry j, we obtain a utilization-implied depreciation rate, $\delta(u_j)$, by applying equation (10) to the industry's utilization data.

[38]We describe the measurement of the these depreciation rates in Section OA.1 of the Online Appendix.

Here, we use the model parameters reported in Table 9. Second, we average these depreciation rates across all industries to obtain an aggregate utilization-implied depreciation rate, $\delta(u_{agg})$. Third, we adjust $\delta(u_{agg})$ to share the same trend as the aggregate depreciation rate from the BEA. We do this by combining the business-cycle component of $\delta(u_{agg})$ with the stochastic trend component of the BEA's aggregate depreciation rate.[39] We obtain the components of each time-series using the Hodrick and Prescott (1997) filter.

In Figure 2 we plot the monthly time-series of $\delta(u_{agg})$ alongside the trend of the BEA's aggregate depreciation rate. By construction, the two time-series share the same trend, but $\delta(u_{agg})$ shows high-frequency business-cycle fluctuations around this common trend. These fluctuations could be important as they amplify the volatility of gross investment rates and can help to reconcile the dynamics of BEA- and Compustat-implied depreciation rates.

5.5 The effect of stochastic depreciation shocks

In this section we pursue an extension of our model, motivated by the empirical evidence in Section 5.4. Specifically, while our baseline model assumes that depreciation rates correlate positively with utilization rates (recall equation (10)), Table 14 shows that these two quantities comove together, but not *perfectly*. As a result, we modify equation (10) to also feature an exogenous shock to the depreciation rate. This implies that a firm's depreciation rate becomes a combination of (i) its choice of utilization rate, and (ii) a stochastic shock. This augmented depreciation function is presented below:

$$\delta(u_{i,t}) = \delta_k + \delta_u \left[\frac{u_{i,t}^{1+\lambda} - 1}{1+\lambda} \right] + d_t, \tag{24}$$

$$d_{t+1} = \rho_d d_t + \sigma_d \varepsilon_{t+1}^{\delta}, \tag{25}$$

where ε_t^{δ} is a standard normal i.i.d. shock to depreciation. Since depreciation shocks can be correlated with aggregate productivity, we consider two extreme cases: shocks that are both perfectly positively and perfectly negatively correlated with aggregate productivity.

We calibrate ρ_d and σ_d such that the largest value of $|d_t|$ in a discrete state space with a truncated support (i.e., 2 standard deviations away from zero) causes the depreciation rate

[39]The third step is optional and meant to ensure both series follow the same trend. An alternative measure of the utilization-implied depreciation rate involves only the first two steps, with similar results.

to change by up to 2.58%. Since the unconditional depreciation rate in the model (δ_k) is 8%, the impact of the largest depreciation shock causes a firm's depreciation rate to change by roughly 33% compared to its unconditional average. Due to the large magnitude of these calibrated depreciation rate shocks, this exercises places an upper bound on the effect that these shocks can have on the utilization premium.

The results of this analysis are reported in Table OA.4.18 of the Online Appendix. The table shows that depreciation shocks that are perfectly positively (negatively) correlated with aggregate productivity decrease (increase) the model-implied utilization spread by 0.60% per annum. In either the case the model-implied spread, which is based on industry-level portfolio returns, falls within the confidence interval of the utilization premium in the data. Since the true correlation between depreciation and utilization rates is unknown, but must necessarily fall within the range of correlations we consider (i.e., $[-1, +1]$), exogenous shocks to depreciation rates do not materially impact the magnitude of the utilization premium.

6 Conclusion

In this study we show empirically and theoretically that flexible capacity utilization – the degree to which a firm uses its production potential – induces economically sizable implications for cross-sectional risk profiles and investment choices. Empirically, we document two facts: (1) A low capacity utilization portfolio earns a higher expected return of about 5% per annum, resulting in a *Utilization Premium*. This fact is established using both industry-level utilization data from the FRB and firm-level proxies for utilization rates based on Compustat data. Utilization predicts returns beyond production-based characteristics, such as book-to-market ratios, tangible and intangible investment, and hiring. (2) There is a monotonically decreasing relation between utilization rates and exposures to aggregate productivity. The low utilization portfolio is more sensitive to changes in aggregate productivity. Theoretically, we show that a production-based asset-pricing model can reconcile these facts. Last but not least, we find that flexible utilization is essential for matching the cross-sectional distribution of investment and stock prices *jointly* in the presence of real options.

Importantly, while we use industry-level data to document the baseline facts, the utilization premium is not simply capturing cross-sectoral heterogeneity. We establish this in five ways. First, Fama and MacBeth (1973) projections show that utilization is an economically significant and distinct predictor of risk premia, controlling for sector-specific fixed effects. Second, the utilization premium exists *within* economic sectors (e.g., among durable manufacturers only). Third, the utilization spread persists when we form portfolios using the growth rate of utilization. This eliminates any industry-specific fixed effects in utilization's level. Fourth, as noted previously, we construct novel proxies for firm-level utilization rates using Compustat data. The premium remains positive when sorting firms into portfolios based on these proxies. Finally, through the lens of our model, we show that ex-ante heterogeneity in parameters related to industry-level differences (e.g., depreciation rates) contributes only marginally to the utilization premium.

The economic rationale for the utilization premium relates to utilization's ability to partially offset disinvestment risk. In the model, downscaling capital in the presence of capital adjustment costs increases firms' exposures to aggregate risk. Lowering utilization allows firms to partially hedge this risk. First, lower capacity utilization implies that firms use their installed machines less intensively, and causes the capital depreciation rate to decrease. This lower depreciation conserves more capital for future periods that are more productive. Second, the decrease in the depreciation rate drops the natural rate of investment and, consequently, reduces the convex adjustment costs required to downscale. Moreover, when selling machines involves paying a fixed cost, firms can substitute selling capital (exercising their real option) by lowering utilization. Overall, low utilization firms are risky because a low utilization rate is indicative of a firm that wants to drop investment, faces high frictions in the market for selling capital, and tries to partially alleviate these frictions through utilization.

Flexible utilization has broader importance for macro-finance models. In a real option setup with fixed utilization, the cross-section of investment rates features too little dispersion and skewness. Furthermore, return spreads are also too small unless capital adjustment frictions are increased, which further distorts investment's distribution. By inducing a time-varying depreciation rate, flexible utilization increases the dispersion and asymmetry in investment's distribution, in line with the data. Matching these properties of investment's distribution is key for cross-sectional asset pricing. When the model-implied investment rates are as dispersed and skewed as their empirical counterparts, the dispersion of firms' risk exposures to aggregate productivity rises. Consequently, a flexible utilization model generates large return spreads, without relying on high exogenous capital adjustment costs.

Flexible utilization also bears implications for the measurement of depreciation rates. First, we confirm the model's prediction that utilization and depreciation rates oscillate together. Second, we show that this observation can be used to construct a high-frequency measure of depreciation. Lastly, we also show that the low unconditional correlation between BEA- and Compustat-based depreciation rates increases when controlling for utilization.

In all, the results in this study demonstrate the economic importance of varying utilization for both expected returns and real quantities. Utilization impacts returns in a sizable way. It offers a way to increase investment's dispersion in production models, without compromising on achieving high risk premia.

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Tables and Figures

Table 1: **Capacity utilization and stock returns: Data**

Portfolio	Value-weighted Mean	Value-weighted SD	Equal-weighted Mean	Equal-weighted SD
Low (L)	13.64	21.23	10.62	21.14
Medium	10.49	16.70	8.20	17.63
High (H)	7.96	20.22	5.18	20.39
Spread	5.67	17.71	5.44	15.51
(L-H)	(2.31)		(2.47)	

The table reports annual returns of portfolios sorted on capacity utilization, as well as the spread between the returns of the Low (L) and the High (H) capacity utilization portfolio. Both value- and equal-weighted portfolio returns are reported. The Mean refers to the average annual return, and SD denotes the standard deviation of annual returns. Returns are annualized by multiplying the average monthly return by 12. Parentheses report Newey and West (1987) t-statistics. All portfolios are formed at the end of each June and are rebalanced annually. The sample is from July 1967 to December 2015.

Table 2: **Exposure of CU-sorted portfolios to aggregate productivity proxies**

Portfolio	Market returns β	Market returns $t(\beta)$	Util.-adjusted TFP β	Util.-adjusted TFP $t(\beta)$	Labor productivity β	Labor productivity $t(\beta)$
Low (L)	1.33	(10.09)	1.17	(2.67)	0.95	(1.87)
Medium	1.23	(12.15)	0.75	(2.18)	0.60	(1.41)
High (H)	1.07	(7.68)	0.77	(1.93)	0.60	(1.28)
Spread (L-H)	0.26	(3.50)	0.40	(1.93)	0.34	(1.97)
Intercept	4.36	(1.78)	4.60	(1.72)	3.34	(1.18)

The table reports the exposures of portfolios sorted on capacity utilization to three different aggregate productivity proxies. The regression is: $Ret^e_{i,t} = \beta_0 + \beta_1 \text{Agg-Proxy}_t + \varepsilon_{i,t}$, where $Ret^e_{i,t}$ is the value-weighted excess return of a portfolio, Agg-Proxy is a proxy of aggregate productivity, and β is the exposure of interest. Agg-Proxy is either (i) excess market returns, (ii) utilization-adjusted TFP growth from Fernald (2012), or (iii) labor productivity growth from the BLS. Monthly returns are aggregated to the quarterly frequency so that each regression is estimated using quarterly data. Newey and West (1987) t-statistics are reported in parentheses, and "Intercept" refers to the annualized value of β_0 (obtained by multiplying β_0 by four) from projecting the utilization spread on each productivity proxy. The sample spans July 1967 to December 2015.

Table 3: **Characteristics of capacity utilization sorted portfolios**

	Low (L)	Medium	High (H)	Diff(L-H)	t(Diff)
Panel A: Portfolio constituents					
CU (%)	67	79	91		
N ($Stocks$)	617	4423	348		
N ($Ind.$)	5	35	4		
Panel B: Portfolio characteristics					
ME ($b)	1.02	0.81	1.08	-0.06	(-0.59)
BE / ME	1.34	1.19	1.13	0.21	(1.81)
ROA	0.02	0.01	0.01	0.00	(0.27)
GP / Assets	0.35	0.34	0.30	0.05	(1.27)
Asset Growth (%)	10.01	11.25	13.04	-3.03	(-1.08)
Inventory Growth (%)	10.29	10.59	12.62	-2.34	(-0.37)
I / K	0.06	0.06	0.09	-0.03	(-2.03)
IVOL (%)	3.18	2.89	2.86	0.32	(1.96)
TFP	0.76	0.73	0.78	-0.02	(-0.51)
Hire Rate (%)	3.95	3.48	5.80	-1.85	(-0.68)
R&D / ME	0.06	0.05	0.05	0.01	(0.97)
Leverage	0.26	0.24	0.26	-0.01	(-0.76)
Debt growth (%)	3.64	2.80	5.32	-1.68	(-1.38)
Equity issue. (%)	4.78	5.19	5.38	-0.60	(-1.46)

The table shows both the composition and characteristics of capacity utilization sorted portfolios. Panel A reports the composition of each portfolio, while Panel B reports industry-level characteristics, averaged across all industries that are assigned to a particular portfolio. All data is annual and is recorded at the end of each June from 1967 to 2015. In Panel A, CU denotes the capacity utilization rate, while N (Stocks) and N (Industries) refer to the average number of individual firms and industries comprising each portfolio, respectively. In Panel B, all statistics are computed as the time-series average of each portfolio's simple firm-level average of a certain characteristic. Details on the construction of each variable are provided in Section OA.1 of the Online Appendix. The column Diff(L-H) refers to the difference between the average characteristics of the low and high capacity utilization portfolios, and t(Diff) is the Newey and West (1987) t-statistic associated with this difference.

Table 4: **Most frequent industry constituents of capacity utilization portfolios**

Industry	Sector	Freq(Extreme)
Panel A: Low capacity utilization portfolio		
Leather and allied product	ND	42.27
Aerospace and miscellaneous transportation eq.	D	41.24
Support activities for mining	MU	37.93
Automobile and light duty motor vehicle	D	29.89
Motor vehicles and parts	D	28.87
Panel B: High capacity utilization portfolio		
Oil and gas extraction	MU	79.31
Plastics material and resin	ND	54.02
Electric power generation, transmission, and distribution	MU	35.05
Mining	MU	34.02
Petroleum and coal products	ND	24.74

The table reports the name of each of the five industries that most frequently populate either the low or the high capacity utilization portfolio. For these industries, the table also reports the frequency, measured as percentage of years over the entire sample period with which each industry is sorted into a particular capacity utilization portfolio. Panel A (Panel B) shows the results for the the low (high) capacity utilization portfolio, and Freq(Extreme) refers to the percentage of years that each industry of interest belongs to the low (high) capacity utilization portfolio. The Sector column reports how each industry is classified into one of three broad categories: durable goods manufacturing (D), nondurable goods manufacturing (ND), or mining or utilities (MU).

Table 5: **Fama-Macbeth regressions**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
CU	-1.66									-1.51	-1.64	-1.53	-1.93	-1.51	-1.42	-1.64	-1.33	-1.80
	(-2.31)									(-2.13)	(-2.27)	(-2.11)	(-2.44)	(-2.12)	(-2.01)	(-2.07)	(-2.01)	(-2.75)
TFP		-1.96								-1.91				-1.66	-1.29	-1.25	1.33	1.32
		(-2.28)								(-2.23)				(-1.94)	(-1.46)	(-1.59)	(2.81)	(2.79)
HIRE			-4.56								-4.46			-3.84	-2.99	-7.22	-5.54	-5.34
			(-3.94)								(-3.91)			(-3.45)	(-2.71)	(-4.24)	(-3.64)	(-3.68)
I/K				-3.73								-3.85			-2.12	-2.66	-2.32	-2.38
				(-3.52)								(-3.78)			(-1.96)	(-2.17)	(-2.47)	(-2.80)
OVER					-3.14								-3.18			-3.52	-2.75	-2.86
					(-3.18)								(-3.14)			(-3.60)	(-2.81)	(-3.13)
OC / AT						3.59											2.15	2.16
						(2.66)											(1.79)	(2.00)
ln(ME)							-3.74										-2.00	-2.12
							(-2.93)										(-1.70)	(-1.86)
ln(B/M)								3.38									3.87	3.89
								(3.86)									(4.11)	(4.30)
RET_{t-1}									-0.23								-1.17	-1.08
									(-0.16)								(-0.79)	(-0.76)
Sector FE	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	Yes
R^2	0.006	0.008	0.005	0.011	0.007	0.016	0.026	0.016	0.014	0.014	0.011	0.017	0.015	0.019	0.027	0.037	0.089	0.110

The table reports the results of Fama-Macbeth regressions in which future excess returns are regressed on current characteristics. In each year t we run the following cross-sectional regression in which the dependent variable is a firm's annual excess return from the start of July in year t to the end of June in year $t+1$, and the independent variables are a vector of the firm's characteristics, $\boldsymbol{X}_t$ measured at the end of June in year t: $R_{i,t\to t+1} = \beta_0 + \boldsymbol{\beta}_t'\boldsymbol{X}_{i,t} + \varepsilon_{i,t\to t+1} \quad \forall t \in \{1967,\ldots,2014\}$. The characteristics considered are capacity utilization (CU), total factor productivity (TFP), the hiring rate (HIRE), the natural investment rate (I/K), capacity overhang (OVER), the ratio of organization capital to assets (OC / AT), the natural logarithm of the market value of equity (ln(ME)), the natural logarithm of the book-to-market (ln(B/M)) ratio, and lagged annual return (RET_{t-1}). After running these cross-sectional regressions we compute the time-series average of each element of the vectors the estimated slope coefficients, $\{\hat{\boldsymbol{\beta}}_t\}_{t=1967}^{2014}$. Each column reports the average slope coefficients for the characteristics of interest. Parenthesis report Newey and West (1987) t-statistics. Columns 1 to 9 of the table show the results when each characteristic is included in a separate univariate regression. Columns 10 to 16 show the results when a subset of characteristics are used in multivariate regressions. In Columns 17 and 18 all characteristics of interest are included in the cross-sectional regressions simultaneously, with column 18 also including sector fixed effects. Each control variable is standardized by dividing it by its unconditional standard deviation. The table also report the time-series average of the R^2 obtained from each set of cross-sectional regressions. The first regression is run in 1967 and the last regression is run in 2014, when the TFP data becomes unavailable.

Table 6: **Capacity utilization spread: inclusion and exclusion of major sectors**

	Only Durable Sector		Excluding Mining & Utilities Sector	
Portfolio	Mean	SD	Mean	SD
Low (L)	15.08	24.23	14.39	21.63
Medium	10.39	22.11	10.73	17.88
High (H)	9.23	23.77	9.12	20.21
Spread	5.85	19.08	5.27	17.31
(L-H)	(2.13)		(2.12)	

The table reports the annual returns of portfolios sorted on the basis of capacity utilization, as well as the spread between the low (L) and high (H) capacity utilization portfolios when specific sectors are included or excluded from the sample. The left panel shows the results when the sample includes only industries that are classified as durable goods manufacturers. The right panel shows the results when the sample excludes all mining industries and utilities. The table reports the average value-weighted return (Mean) and standard deviation (SD) of each portfolio's returns. t-statistics, reported in parentheses, are computed using Newey and West (1987) standard errors. The sample period is between July 1967 to December 2015.

Table 7: **Capacity utilization spread: sorting on growth rates**

	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low (L)	14.49	21.41	11.53	21.92
Medium	10.05	16.63	7.78	17.59
High (H)	9.69	20.59	5.79	20.93
Spread	4.80	16.93	5.74	16.41
(L-H)	(2.00)		(2.45)	

The table reports the annual returns of three portfolios sorted on the basis of capacity utilization growth, as well as the spread between the low (L) and high (H) utilization growth portfolios. The construction of the portfolios is identical to the benchmark analysis, except that portfolios are sorted on the basis of the growth rate of utilization rather than the level of utilization. The growth rate of utilization is measured between March of years t and $t-1$. Mean refers to the average annual return and SD denotes the standard deviation of annual raw returns, and the parentheses report t-statistics computed using Newey and West (1987) standard errors. The portfolios are formed at the end of each June from 1968 to 2015 and are rebalanced annually, with portfolio returns spanning July 1968 to December 2015

Table 8: **Capacity utilization spread: proxy for firm-level utilization rates**

	Utilization		De-meaned utilization	
Portfolio	Mean	SD	Mean	SD
Low (L)	12.65	19.92	11.92	17.67
Medium	11.98	15.93	11.80	16.50
High (H)	7.66	21.58	6.77	22.08
Spread	4.98	15.39	5.14	15.48
(L-H)	(2.32)		(2.02)	

The table reports the annual value-weighted returns of portfolios sorted on the basis of estimated firm-level capacity utilization rates, as well as the spread between the low (L) and high (H) utilization portfolios. The firm-level proxy for utilization is constructed following the procedure outlined in Section 2.7.2. The table reports the average value-weighted return (Mean) and standard deviation (SD) of each portfolio's returns, and all portfolios are formed by following the procedure described in Section 2.2. t-statistics, reported in parentheses, are computed using Newey and West (1987) standard errors. The sample period is between July 1967 to December 2015.

Table 9: **Model calibration**

Symbol	Description	Value
Stochastic processes		
ρ_x	Persistence of aggregate productivity	0.922
σ_x	Conditional volatility of aggregate productivity	0.014
$\bar{z}$	Long-run average of idiosyncratic productivity	-0.163
ρ_z	Persistence of idiosyncratic productivity	0.600
σ_z	Conditional volatility of idiosyncratic productivity	0.300
β	Time discount factor	0.988
γ_0	Constant price of risk	3.375
γ_1	Time-varying price of risk	-8.800
Technology		
α_k	Capital share	0.333
α_l	Labor share	0.667
θ	Returns to scale of production	0.950
δ_k	Fixed capital depreciation rate	0.080
δ_u	Slope of depreciation rate	0.092
λ	Elasticity of marginal depreciation	3.000
ω	Sensitivity of wages to aggregate productivity	0.200
ϕ	Adjustment cost parameter	1.500
f	Fixed cost parameter	0.028

This table reports the calibrated parameter values of the production-based asset pricing model described in Section 3.1.

Table 10: **Model-implied moments**

Variable	Data	Model
Panel A: Real quantities		
Volatility of firm-level investment rate (time-series)	0.14	0.14
Volatility of firm-level investment rate (cross-sectional)	0.16	0.11
AC(1) of firm-level investment rate	0.52	0.58
AC(2) of firm-level investment rate	0.26	0.38
Skewness of firm-level investment rate (time-series)	0.67	0.66
Skewness of firm-level investment rate (cross-sectional)	1.89	1.19
Inter-decile range of investment rate	0.32	0.22
Volatility of aggregate capacity utilization level	4.09	4.15
Autocorrelation of aggregate capacity utilization level	0.65	0.92
Volatility of aggregate sales growth	6.58	7.55
Autocorrelation of aggregate sales growth	0.46	0.41
Panel B: Asset prices		
Real risk-free rate	1.19	1.21
Excess market return	6.28	5.39
Volatility of excess market return	17.20	20.89
Autocorrelation of excess market return	-0.05	-0.00
Book-to-market spread	3.71	3.76
Investment spread	3.70	4.27

The table shows model-implied moments, obtained by simulating 1,000 firms for 40,000 periods (years), alongside their empirical counterparts, computed using data from 1967 to 2015. Panel A displays moments associated with firm-level investment rates, aggregate capacity utilization rates, and aggregate sales growth rates, while Panel B reports asset-pricing moments related to the risk-free rate, equity premium, and the book-to-market and investment spreads. In each panel AC(1) and AC(2) refer to the first- and second-order autocorrelation of the given variable.

Table 11: **Capacity utilization and stock returns: model**

Portfolio	Population $E\left[R^{CU}\right]$	Population β	Short sample $E\left[R^{CU}\right]$
Panel A: Firm-level analysis			
Low (L)	9.53	1.34	9.86 [5.47, 18.35]
Medium	6.83	1.23	7.11 [3.28, 14.56]
High (H)	4.41	1.09	4.64 [1.21, 11.18]
Spread (L-H)	5.12	0.25	5.21 [3.79, 7.09]
Panel B: Industry-level analysis			
Low (L)	9.05	1.34	9.01 [4.24, 16.87]
Medium	6.93	1.25	6.93 [3.14, 14.07]
High (H)	5.11	1.17	4.97 [-0.10, 12.66]
Spread (L-H)	3.94	0.17	4.04 [0.38, 8.75]

The table reports the average model-implied annual value-weighted returns of portfolios sorted on capacity utilization at both the firm-level and the industry-level. The table also shows the exposure of each capacity utilization portfolio to the aggregate market return (β). As in the empirical analysis, a firm or industry is sorted into the high (low) utilization portfolio if its level of capacity utilization is above (below) the 90^{th} (10^{th}) percentile of the cross-sectional distribution of capacity utilization rates in the previous period. In Panel A, which reports firm-level moments, population moments are obtained from one simulation of 1,000 firms for 40,0000 periods (years). Short-sample moments are obtained by averaging moments across 500 simulations of 4,000 firms for 50 periods (years). In Panel B, industry-level returns are simulated using the procedure described in Section 4.1. Here, population moments are obtained from one simulation of 50 industries for 40,000 periods (years). Similarly, short sample moments are obtained by averaging moments across 500 simulations of 50 industries for 50 periods (years). To compute β in the model, the volatility of market returns in the model is scaled to match the volatility of market returns in the data. Finally, square brackets associated with the short sample simulations report the 95% confidence interval related to each moment across the 500 Monte Carlo simulations of the economy.

Table 12: **Capacity utilization spread: sensitivity to ex-ante heterogeneity**

	Heterogeneous ϕ		Heterogeneous λ		Heterogeneous δ_k	
Portfolio	$E\left[R^{CU}\right]$	β	$E\left[R^{CU}\right]$	β	$E\left[R^{CU}\right]$	β
Low (L)	9.82	1.21	9.60	1.19	9.71	1.26
Medium	6.99	1.10	6.99	1.09	6.15	1.10
High (H)	4.52	0.97	4.23	1.01	3.60	0.97
Spread (L-H)	5.30	0.23	5.37	0.18	6.11	0.29

The Table show the model-implied capacity utilization spread when firms in the economy show ex-ante heterogeneity in some parameter of interest x. The parameter of interest x is either ϕ, the quadratic capital adjustment costs, λ, the elasticity of depreciation to utilization, or δ_k, the average depreciation rate. For each parameter, denote by x_0 be its value in the benchmark calibration, as shown in Table 9. Let N be the number of simulated firms in the economy. We set N to 1,000, as in Table 11. We solve the model twice: once when the parameter x is increased by 100% to $x_U = 2x_0$, and once when the parameter x is decreased by 100% to $x_D = 0.5x_0$. We simulate $N/2$ firms implied by the model solved for parameter x_U, and simulate $N/2$ firms implied by the solution for x_D. Each simulation encompasses 40,000 periods. We then combine the two samples, and sort all firms on the basis of utilization in an identical fashion to Table 11. A firm or industry is sorted into the high (low) utilization portfolio if its level of capacity utilization is above (below) the 90^{th} (10^{th}) percentile of the cross-sectional distribution of capacity utilization rates in the previous period. To compute β in the model, the volatility of market returns in the model is scaled to match the volatility of market returns in the data.

Table 13: **Model-implied moments across alternative calibrations of the model**

Row	Model	Time-series				Cross-sectional		Risk premia	
		$\sigma_{TS}(ik)$	$S_{TS}(ik)$	$\rho_1(ik)$	$\sigma(u)$	$\sigma_{CS}(ik)$	$S_{CS}(ik)$	$E\left[R^{bm}\right]$	$E\left[R^{ik}\right]$
	Data	0.14	0.67	0.52	4.09	0.16	1.89	3.71	3.70
	Panel A: Sensitivity to utilization (λ)								
	Baseline without utilization								
(1)	($\lambda \to \infty$)	0.11	-0.09	0.64	-	0.07	0.11	2.93	2.30
	Baseline								
(2)	($\lambda = 3$)	0.14	0.66	0.58	4.15	0.11	1.19	3.76	4.27
	Different λ								
(3)	Very low ($\lambda = 2.00$)	0.16	1.12	0.56	6.24	0.13	1.60	4.11	4.69
(4)	Low ($\lambda = 2.90$)	0.14	0.69	0.58	4.30	0.11	1.22	3.78	4.30
(5)	High ($\lambda = 3.10$)	0.14	0.63	0.58	4.02	0.11	1.16	3.74	4.24
(6)	Very high ($\lambda = 13.00$)	0.12	-0.05	0.62	0.96	0.08	0.39	3.18	3.53
	Panel B: Sensitivity to adjustment costs (ϕ)								
	Different ϕ and fixed utilization								
(7)	Very low ($\phi = 0.75$)	0.19	0.50	0.59	-	0.12	0.06	2.04	2.03
(8)	Low ($\phi = 1.40$)	0.12	-0.04	0.63	-	0.08	0.10	2.84	2.28
(9)	High ($\phi = 1.60$)	0.11	-0.14	0.64	-	0.07	0.11	3.00	2.34
(10)	Very high ($\phi = 3.00$)	0.06	-0.67	0.65	-	0.04	0.13	3.72	2.40
	Different ϕ and flexible utilization								
(11)	Very low ($\phi = 0.75$)	0.21	0.73	0.56	4.78	0.15	0.81	2.76	3.62
(12)	Low ($\phi = 1.40$)	0.15	0.65	0.58	4.23	0.11	1.15	3.66	4.20
(13)	High ($\phi = 1.60$)	0.14	0.67	0.58	4.09	0.10	1.23	3.85	4.34
(14)	Very high ($\phi = 3.00$)	0.10	0.92	0.57	3.40	0.08	1.66	4.77	5.06

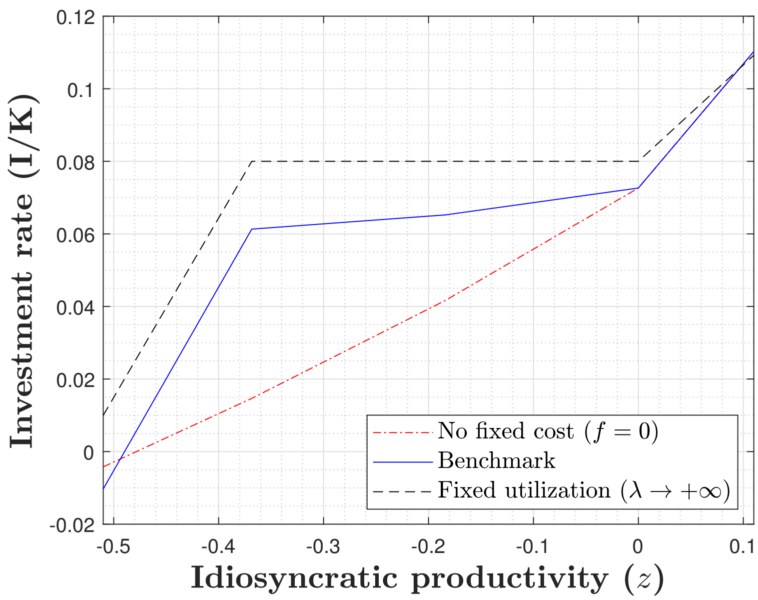
The table reports model-implied population moments related to the time-series and cross-section of investment rates, as well as risk premia, under various calibrations. The table reports the time-series volatility ($\sigma_{TS}(ik)$), skewness ($S_{TS}(ik)$), and first-order autocorrelation ($\rho(ik)$) of firm-level investment rates, the time-series volatility of utilization ($\sigma(u)$), as well as the cross-sectional dispersion ($\sigma_{CS}(ik)$) and skewness ($S_{CS}(ik)$) of investment rates. In addition, the table also reports the value premium ($E\left[R^{bm}\right]$) and investment premium ($E\left[R^{ik}\right]$) obtained by sorting the cross-section of model-implied returns association with each calibration on book-to-market ratios and investment rates, respectively. These risk premia are expressed as an annualized percentage. Each alternative calibration is identical to the benchmark calibration in all ways except for altering the elasticity of marginal depreciation (λ) or the quadratic capital adjustment cost (ϕ). All moments are based on a simulations of 1,000 firms over 40,0000 periods (years). Finally, the top row of the table also reports the empirical counterpart of each moment.

Table 14: **Empirical relation between capacity utilization and depreciation rates**

	(1)	(2)	(3)	(4)	(5)	(6)
β_{UTIL}	0.30	0.30			0.28	0.28
	(3.11)	(3.14)			(2.80)	(2.83)
β_{COMP}			0.03	0.03	0.13	0.14
			(3.50)	(3.53)	(3.54)	(3.58)
Industry FE	No	Yes	No	Yes	No	Yes
R^2	0.09	0.09	0.02	0.02	0.10	0.10

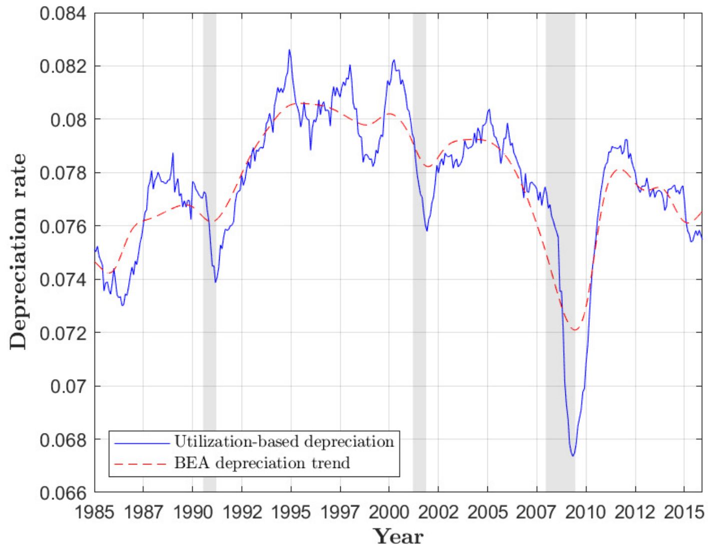
The table reports the empirical relation between the industry-level capacity utilization rate, industry-level depreciation rate from the BEA, and industry-level depreciation rate from Compustat. In each specification considered in the table we run projections of the log-growth rate of BEA-implied depreciation on the log-growth rates of capacity utilization and Compustat-implied depreciation rates, and standardize all variables for ease of interpretation. Columns (1), (3), and (5) of the table estimated pooled-OLS regressions, whereas columns (2), (4), and (6) of the table estimate panel regressions including industry fixed effects. t-statistics, reported in parentheses, and computed using standard errors clustered at the industry level. Finally, the time span underlying the regressions is from January 1967 to December 2015.

Figure 1: **Model-implied investment policy**



The figure shows the optimal investment rate policy (I/K) as a function of idiosyncratic productivity (z). Capital and aggregate productivity are set at their stochastic steady-state values, and we focus on z around the region in which the fixed cost of disinvestment may apply. We consider the I/K policy under three versions of our model: (1) The benchmark model (solid blue line), (2) the model without fixed costs (i.e., $f = 0$) (the dashed red line), and (3) the model with fixed utilization (i.e., $\lambda \to +\infty$).

Figure 2: **Utilization-based high-frequency depreciation rate**



The figure shows a high-frequency measure of the aggregate depreciation rate. The figure is obtained by computing the annual aggregate depreciation rate for the United States using the average industry-level annual depreciation rates reported by the BEA, and applying the Hodrick and Prescott (1997) (HP, hereafter) filter to this aggregate time series. The trend component of this HP filtered time series (denoted by the red dashed line) is retained, and is converted to a monthly time-series by using a cubic interpolation between low-frequency annual observations. Next, we estimate the high-frequency aggregate depreciation rate using monthly industry-level capacity utilization data, equation (10), and the parameters of our model reported in Table 9, and averaging these model-implied depreciation rates across industries. We then apply the HP filter to this time-series of high-frequency depreciation rates and retain the business-cycle component of this time series. Finally, we obtain the high-frequency measure of the aggregate depreciation rate by adding the business-cycle component for the second step of this procedure to the trend component from the first step of this procedure. The figure reports the time series of the high-frequency depreciation rate from 1985, the beginning of the Great Moderation, to 2015.

A Internet appendix

OA.1 Variable description and construction

Asset growth. Asset growth is calculated as the year-on-year annual growth rate of total assets (Compustat Annual item AT) betweens years $t-1$ and t. This definition of asset growth is drawn from Cooper, Gulen, and Schill (2008).

Book-to-market (BE/ME). A firm's book-to-market ratio is constructed by following Daniel and Titman (2006). Book equity is defined as shareholders' equity minus the value of preferred stock. If available, shareholders' equity is set equal to stockholders' equity (Compustat Annual item SEQ). If stockholders' equity is missing, then common equity (Compustat Annual item CEQ) plus the par value of preferred stock (Compustat Annual item PSTK) is used instead. If neither of the two previous definitions of stockholders' equity can be constructed, then shareholders' equity is the difference between total assets (Compustat Annual item AT) and total liabilities (Compustat Annual item LT). For the value of preferred stock we use the redemption value (Compustat Annual item PSTKRV), the liquidating value (Compustat Annual item PSTKL), or the carrying value (Compustat Annual item PSTK), in that order of preference. We also add the value of deferred taxes and investment tax credits (Compustat Annual item TXDITC) to, and subtract the value of post retirement benefits (Compustat Annual item PRBA) from, the value of book equity if either variable is available. Finally, the book value of equity in the fiscal year ending in calendar year $t-1$ is divided by the market value of common equity from December of year $t-1$.

Capacity. The capacity estimate measures the maximum amount of output that an industry can produce, assuming the sufficient availability of inputs to production and a realistic work schedule. The FRB relies on a variety of sources to determine the capacity of each industry. The primary source of capacity data for manufacturing industries, which make up the bulk of our sample, is currently the Quarterly Survey of Plant Capacity Utilization (QPC). For approximately 20% industries, including a subset of manufacturers, capacity is reported in physical units obtained from government or trade sources, such as the United States Geological Survey. Finally, for a small proportion of industries for which neither of the aforementioned data sources are available, the FRB estimates capacity based on trends through peaks in production. Gilbert, Morin, and Raddock (2000) and Board of Govenors of the Federal Reserve System (2017) provide overviews of how the FRB measures capacity.

Capacity overhang (OVER). We construct a monthly measure of capacity overhang by following the procedure described by Aretz and Pope (2018). In particular we recursively estimate equation (1) of Aretz and Pope (2018) using total assets (Compustat Annual item AT) as our measure of installed capacity.

Debt growth. We measure the growth rate of a firm's debt by calculating the annual percentage change in outstanding total debt, expressed in real terms. We define total real debt as the sum of long-term debt (Compustat Annual item DLTT) and debt in current liabilities (Compustat Annual item DLC), scaled by the value of the consumer price index. When computing this quantity we require firms to have at least \$10m of debt outstanding in year $t-1$.

Depreciation rate (BEA implied). To compute the BEA-implied depreciation rate we take the GDP-weighted average of the industry-level depreciation rates associated with equipment and structures.

Depreciation rate (Compustat implied). We compute Compustat-implied industry-level depreciation rates by first constructing firm-level depreciation rates. A firm's depreciation rate is defined as the firm's depreciation expense (Compustat annual item DP) minus the firm's amortization (Compustat annual item AM) scaled by net property, plant, and equipment (Compustat annual item PPENT). We then aggregate these firm-level depreciation rates to the industry-level by computing the value-weighted depreciation rate across all firms assigned to a particular industry.

Equity issuance. Gross equity issuance is defined as the sale of common and preferred stock (Compustat Annual item SSTK) divided by the lagged value of book equity, as per Belo et al. (2018).

Gross profitability (GP). Consistent with Novy-Marx (2013), gross profitability is calculated as total revenue (Compustat Annual item REVT) minus the cost of goods sold (Compustat Annual item COGS), divided by total assets (Compustat Annual item AT).

Hiring rate. The hiring rate is computed following Belo et al. (2014). Specifically, the hiring rate in year t is the change in the number of employees (Compustat Annual item EMP) from year $t-1$ to year t, divided by the mean employees over years $t-1$ and t.

Idiosyncratic volatility (IVOL). Idiosyncratic volatility is computed in accordance with Ang et al. (2006). At the end of month t, a firm's idiosyncratic volatility over the past month is obtained by regressing its daily excess returns on the Fama and French (1993) factors, provided there are at least 15 valid daily returns in the month. Idiosyncratic volatility is then defined as the standard deviation of the residuals from the aforementioned regression.

Intangible investment rate (R&D / ME). We follow Lin (2012) and define a firm's intangible investment rate as the firm's R&D expense (Compustat Annual item XRD) divided by the firm's market capitalization.

Inventory growth. The inventory growth rate is defined following Belo and Lin (2012). That is, we compute the annual percentage change in each firm's inventory holdings (Compustat Annual item INVT) after converting the value of inventorites to real terms.

Investment rate. We follow Stambaugh and Yuan (2017) and compute the investment rate as the change in gross property, plant, and equipment (Compustat Annual item PPEGT) plus the change in inventory (Compustat Annual item INVT) between years $t-1$ and t, divided by the value of total assets (Compustat Annual item AT) in year $t-1$.

Leverage. We define a firm's leverage ratio as long-term debt (Compustat Annual item DLTT) plus debt in current liabilities (Compustat Annual item DLC) divided by total assets (Compustat Annual item AT).

Market capitalization. A firm's end of month t market capitalization is computed as the firm's end of month t stock price (CRSP Monthly item PRC) multiplied by the firm's number of shares outstanding (CRSP Monthly item SHROUT).

Natural investment rate. Following Belo et al. (2014) the natural rate of investment is computed as capital expenditure (Compustat Annual item CAPX) minus the sales of property, planet, and equipment (Compustat Annual item SPPE) scaled by the average net property, planet, and equipment in years t and $t-1$ (Compustat Annual item PPENT). Missing values of SPPE are set to zero.

Organizational capital (OC). We construct the stock of a firm's organizational capital by following the perpetual inventory inventory method described by Eisfeldt and Papanikolaou (2013). That is, we recursively accumulate a firm's real selling, general and administrative expenses (Compustat Annual item XSGA) over time, and scale the stock of organizational capital by the firm's total assets (Compustat Annual item AT).

Return-on-assets (ROA). Following Imrohoroglu and Tuzel (2014) return on assets (ROA) is computed as net income before extraordinary items (Computat Annual item IB) minus preferred dividends (Compustat Annual item DVP), if available, plus deferred income taxes (Compustat Annual item TXDI), if available, scaled by total assets (Compustat Annual item AT).

TechMark. Recalling equation (29), total factor productivity (TFP) is comprised of three distinct components: technology, time-varying markups, and time-varying capacity utilization rates. We isolate the components of TFP related to technology and markups, referred to as "TechMark," as follows. First, we obtain firm-level estimates of the natural logarithm of TFP from Imrohoroglu and Tuzel (2014). We refer to this variable as $\ln(\mathrm{TFP}_{i,t})$. Next, we assign industry-level capacity utilization rates to individual firms by following the matching algorithm described in Section OA.3.2. We take the natural logarithm of these firm firm-level capacity utilization rates, and denote this quantity $\ln(\mathrm{CU}_{i,t})$. Finally, we define the TechMark variable for firm i at time t as $\text{TechMark}_{i,t} = \ln(\text{TFP}_{i,t}) - \ln(\text{CU}_{i,t})$.

Total factor productivity (TFP). The firm-level estimates of TFP are drawn from Imrohoroglu and Tuzel (2014).

OA.2 Capacity utilization data and summary statistics

The public report on industrial capacity utilization covers 57 industries. These industries are defined at different levels of aggregation ranging from two- to six-digit North American Industry Classification System (NAICS) codes. Specifically, 12 of the industries are crude aggregates that span *multiple* two-digit NAICS codes. For example, one of these 12 aggregates includes the average capacity utilization rate of all manufacturers in the U.S. We remove these 12 crude aggregates from our benchmark sample for two reasons. First, these aggregates do not provide new information as they are spanned by more granularly defined sub-industries that are also included in the sample. Second, these aggregates represents a considerable proportion of total market value and would consequently dominate the returns of the value-weighted portfolios we form in Section 2. Removing these 12 crude aggregates leaves us with a benchmark cross-section of 45 industries that features a mix of durable manufacturers, nondurable manufacturers, and miners and utilities.[40]

As the 45 industries included in the benchmark sample are defined from the relatively coarse two-digit NAICS code level to the most granular six-digit NAICS code level, the benchmark cross-section includes a number of overlapping industries.[41] For instance, the capacity utilization rate of food manufacturers is included in the utilization rate of two industries reported by the FRB: "Food," as well as "Food, beverage, and tobacco." Since removing overlapping industries from our benchmark sample would significantly reduce the number of cross-sectional assets, lower statistical power, and make certain asset pricing tests, such as portfolio double sorts, infeasible, we deal with this overlap in three ways. First, we ensure that our empirical results are valid using both value- and equal-weighted portfolio returns. Second, we verify that our results are not driven by any particular industry that dominates the sample. Third, we also remove the industries that overlap with others and conduct our baseline empirical tests in a sub-sample of 24 distinct industries, each of which corresponds to a unique three-digit NAICS code. Following the example above, this set of

[40] A list of these 45 industries, along with each industry's sectoral affiliation, is provided in Table OA.2.1 of the Online Appendix.

[41] In particular, our final sample consists of one sector defined at the two-digit NAICS level, 27 subsectors defined at the three-digit NAICS level, 13 industry groups defined at the four-digit NAICS level, two industries defined at the five-digit NAICS level, and two U.S. industries defined at the six-digit NAICS level. In Section OA.3 we ensure that our results are robust to this heterogeneity in classification levels.

distinct industries includes both "Food"' and "Beverage and Tobacco" manufacturers, but excludes the composite index that covers both groups of manufacturers.[42]

Monthly capacity utilization data for 32 industries is available beginning in January 1967, and data for an additional 25 industries becomes available in January 1972.[43] The capacity utilization data we collect ends in December 2015. Consequently, we set the time frame of our analysis from January 1967 to December 2015. As a robustness check we verify that our results also hold when we only consider the most recent half of the sample period, when capacity utilization data is available for the entire cross-section of 45 industries.[44]

OA.2.1 Summary statistics

Below, we describe the properties of the aggregate capacity utilization rate and report summary statistics related to the cross-section of industry-level utilization rates.

Figure OA.2.1 shows the annual growth rate of aggregate capacity utilization over the sample period. The figure shows that capacity utilization fluctuates significantly over time and that the growth rate of aggregate utilization is procylical. The aggregate utilization rate drops during recessions, particularly during the Great Recession. The growth rate of aggregate capacity utilization tends to slightly lead the business cycle, and has often served as an early warning for recessions. In five out of the seven recessions during our sample period the growth rate of utilization begins to drop prior to the start of the NBER defined recession. The growth rate of capacity utilization increases during the technological revolution of the late 1990's, the housing bubble, and the recovery from the Great Recession.

As illustrated by equation (1), the capacity utilization rate is a combination of both industrial production and capacity. The former variable is studied extensively in the macroeconomic and finance literature, and features prominently in the context of asset pricing. For instance, Cooper et al. (2008) document a premium for firms with lower total asset growth. The growth rate of assets is directly linked to firms' output, and is consequently captured by the FRB's measure of industrial production. To establish the empirical novelty in examining capacity utilization, we examine the extent to which utilization fluctuates independently of industrial production using the following projection:

$$\Delta CU_t = \beta_0 + \beta_1 \Delta IP_t + \varepsilon_t. \tag{26}$$

[42] These distinct industries are listed in Table OA.2.1 of the Online Appendix and correspond to the entries for which the overlap indicator is marked as "No."

[43] There are only 11 monthly time-series reported between January 1948 to December 1966. As eleven industries is a very small cross-section, we do not consider the pre-1967 period in our benchmark sample.

[44] The first year in which data is available for each industry in the sample is reported in the rightmost column of Table OA.2.1 in the Online Appendix.

Here, ΔCU_t (ΔIP_t) is annual growth rate of aggregate capacity utilization (industrial production), and the residual ε_t captures the component of capacity utilization that is orthogonal to industrial production. Figure OA.2.1 also displays this orthogonal component over the sample period. The dynamics of this orthogonal component do not appear to reflect the dynamics of a white noise process. ε_t is smoother than utilization growth, and changes in ε_t are largely procylical. Similar to utilization growth, ε_t tends to drop during NBER recessions. In some instances the orthogonal component also deviates significantly from capacity utilization growth. For example, during the technology boom of mid-1990's, the orthogonal component declines whereas capacity utilization increases. The orthogonal component drops due to an acceleration in the growth of capacity that was likely facilitated by the technological advancements of the era (Bansak, Morin, and Starr, 2007).

Table OA.2.2 reports summary statistics for the capacity utilization rates of each sector in our benchmark sample. The average rate of aggregate capacity utilization rate is 79.91%. This figure for the U.S. is close to the average capacity utilization rates of 81.17%, 84.69%, and 82.49% for the Euro Zone, China, and Israel, respectively.[45]

The majority of the capacity utilization data in the sample pertains to the manufacturing sector, with an almost even split between the number of durable and nondurable manufacturing industries. The mean annual utilization rate is 77.39% (80.09%) for durable (nondurable) manufacturers. Each of these rates is statistically indistinguishable from the average rate of capacity utilization across all industries in the sample. The fact that the average capacity utilization rate of the manufacturing sector, and of the durable and nondurable manufacturing subsectors, is not statistically different from the U.S. average alleviates the concern that our results are driven by ex-ante heterogeneity between sectors.

Among mining industries and utilities the average capacity utilization rate is 84.13%. This average rate is slightly higher than, and statistically different from, the average rate across all industries. Due to this difference in average capacity utilization rates we verify that our empirical results are robust to excluding mining industries and utilities from our sample. We also verify that our results still hold when we conduct tests using the growth rate of capacity utilization that eliminates differences in levels by construction. The results of both of these tests are reported in Section OA.3.

Table OA.2.2 also reports the volatility and autocorrelation of utilization for the different sectors in our sample. The volatility of the capacity utilization rate is comparable across sectors and ranges from 6.67% per annum for mining to 8.29% per annum for durables. The

[45] See `https://www.dallasfed.org/institute/oecd` for data on these capacity utilization rates, as recorded by the Organization for Economic Cooperation and Development (OECD) and made available by the Federal Reserve Bank of Dallas.

autocorrelation ranges from 0.52 to 0.61, with an all-industry mean of 0.58. These statistics affirm the notion that the level of utilization follows similar dynamics regardless of sector.

Overall, Table OA.2.2 shows that the *unconditional* average rate of capacity utilization is only slightly different between sectors. In particular, most differences between the average utilization rate of a sector and the average aggregate utilization rate are statistically indistinguishable from zero. In contrast to these unconditional differences, the asset pricing tests we conduct rely on *conditional* variation in utilization rates. In other words, our tests exploit the fact that the relative ranking of industries in terms of capacity utilization changes over time. Untabulated results show that if we assume that utilization rates are constant over time, and try to utilize the small unconditional differences in the average rate of capacity utilization between industries to perform the empirical tests, our results cease to hold.

Finally, Table OA.2.3 shows the correlation between capacity utilization and other industry-level production-based characteristics for the average industry in our sample. The characteristics considered include book-to-market, TFP, the hiring rate, sales-to-assets, and the investment rate. While utilization has a positive correlation with productivity, hiring, sales, and investment, these average correlation are fairly low. For example, the average correlation between the investment rate and utilization is only 0.16. This suggests that varying utilization constitutes a separate degree of freedom for managers to smooth dividends, and that any interaction between utilization and expected returns is likely to be independent of the well-established book-to-market and investment rate effects on risk premia.

Table OA.2.1: **Sample composition and industry specification**

Industry name	Sector	Overlap	Start year
Nonmetallic mineral product	D	No	1967
Primary metal	D	No	1967
Fabricated metal product	D	No	1967
Machinery	D	No	1967
Transportation equipment	D	No	1967
Motor vehicles and parts	D	Yes	1967
Aerospace and miscellaneous transportation eq.	D	Yes	1967
Furniture and related product	D	No	1967
Computers, communications eq., and semiconductors	D	Yes	1967
Wood product	D	No	1972
Iron and steel products	D	Yes	1972
Computer and electronic product	D	No	1972

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Table OA.2.1 – Continued from the previous page

Industry name	Sector	Overlap	Start year
Computer and peripheral equipment	D	Yes	1972
Communications equipment	D	Yes	1972
Semiconductor and other electronic component	D	Yes	1972
Electrical equipment, appliance, and component	D	No	1972
Automobile and light duty motor vehicle	D	Yes	1972
Miscellaneous	D	No	1972
Food, beverage, and tobacco	ND	Yes	1967
Leather and allied product	ND	No	1967
Paper	ND	No	1967
Petroleum and coal products	ND	No	1967
Chemical	ND	No	1967
Plastics and rubber products	ND	No	1967
Food	ND	No	1972
Beverage and tobacco product	ND	No	1972
Textile mills	ND	No	1972
Textiles and products	ND	Yes	1972
Textile product mills	ND	No	1972
Apparel	ND	No	1972
Apparel and leather goods	ND	Yes	1972
Printing and related support activities	ND	No	1972
Synthetic rubber	ND	Yes	1972
Plastics material and resin	ND	Yes	1972
Artificial and synthetic fibers and filaments	ND	Yes	1972
Mining	MU	No	1967
Metal ore mining	MU	Yes	1967
Nonmetallic mineral mining and quarrying	MU	Yes	1967
Electric power generation, transmission, and distribution	MU	Yes	1967
Electric and gas utilities	MU	Yes	1967
Natural gas distribution	MU	Yes	1967
Coal mining	MU	Yes	1967
Oil and gas extraction	MU	No	1972
Mining (except oil and gas)	MU	No	1972
Support activities for mining	MU	No	1972

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Table OA.2.1 – Continued from the previous page

Industry name	Sector	Overlap	Start year

The table lists the industries for which capacity utilization data is available at FRED. This set of industries comprises our benchmark sample. For each industry, the table specifies its name, its sector (D denotes the durable sector, ND denotes the nondurable sector, and MU refers to the mining and utilities sector), whether certain industry constituents overlap with other industries in the sample, and the first year in which the industry appears in the sample. All data ends at December 2015.

Table OA.2.2: **Summary statistics of the capacity utilization rate by sector**

Sector	N	Mean	t(Sector-All)	SD	AC(1)
All industries	45	79.91	–	7.38	0.58
Manufacturing	35	78.70	(-0.75)	7.58	0.57
Durable	18	77.39	(-1.58)	8.29	0.52
Nondurable	17	80.09	(0.12)	6.83	0.61
Mining and utilities	10	84.13	(2.35)	6.67	0.60

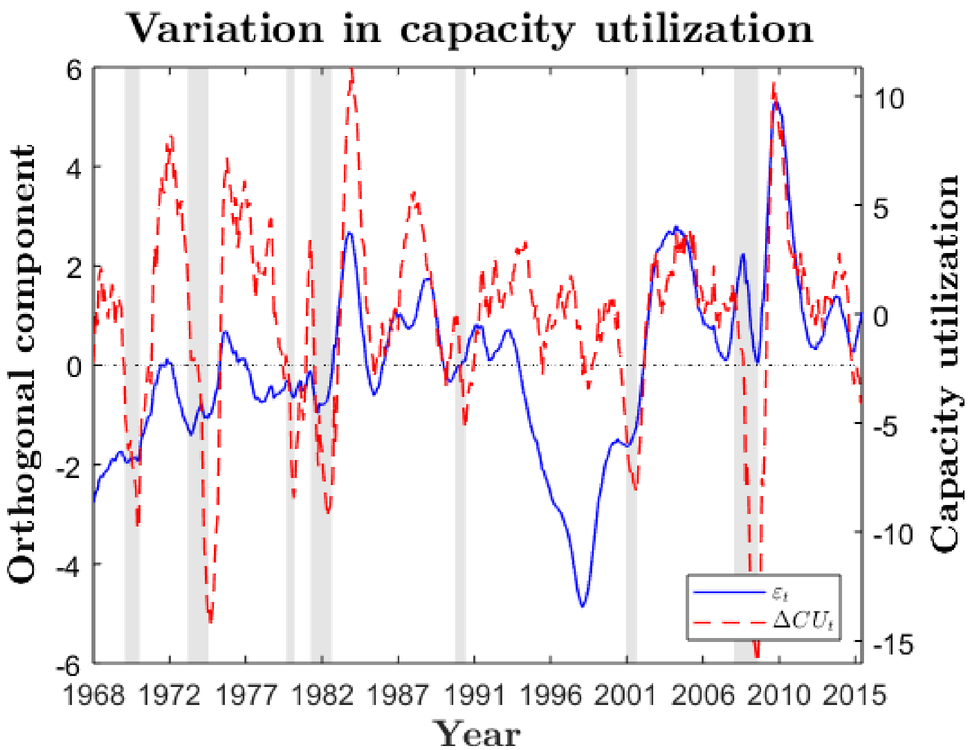
The table reports the mean, standard deviation (SD), and autocorrelation (AC(1)) of the annual capacity utilization rates for each sector in the sample. N represents the number of industries within each sector for which a time-series of capacity utilization data available on FRED. The column t(Sector-All) shows the Newey and West (1987) t-statistic, in parentheses, for the difference in the average capacity utilization rate between the sector denoted in the leftmost column and the average capacity utilization rate across all industries (the top row). The data spans the period 1967 to 2015.

Table OA.2.3: **Average industry-level correlation between production-based characteristics**

	CU	BE / ME	TFP	Hire Rate	Sales / Assets	I / K
CU	1.00	-0.15	0.11	0.13	0.15	0.16
BE / ME		1.00	0.04	-0.26	0.26	-0.00
TFP			1.00	0.23	0.29	0.48
Hire Rate				1.00	0.05	0.53
Sales / Assets					1.00	0.27
I / K						1.00

The table shows the correlation between pairs of industry-level characteristics, averaged over all industries in the sample. The characteristics are the capacity utilization rate (CU), the book-to-market ratio (BE/ME), total factor productivity (TFP), the hiring rate (Hire Rate), the ratio of sales-to assets (Sales / Assets), and the investment rate (I/K). At the end of each June from 1967 to 2015, each industry-level characteristic is constructed as the simple average of the characteristic of interest over all firms that belong to the industry at the point in time. For each industry, we then compute the correlation between industry-level characteristic X and industry-level characteristic Y over the sample period, and report the average value of this correlation across all industries in the sample. The data is annual and runs from 1967 to 2015. Additional details on the construction of each variable are provided in Section OA.1 of the Online Appendix.

Figure OA.2.1: **Capacity utilization: orthogonality from industrial production**



The figure shows the time-series of aggregate capacity utilization growth (dashed red line), as well as the component of capacity utilization growth that is orthogonal to industrial production growth (solid blue line). The orthogonal component of capacity utilization component is obtained from the residuals of the following projection: $\Delta CU_t = \beta_0 + \beta_1 \Delta IP_t + \varepsilon_t$, where CU is aggregate capacity utilization, IP is industrial production, and ε_t is the component of capacity utilization that is orthogonal to industrial production. The horizontal axis shows years and grey shaded regions denote NBER recessions. The right (left) vertical axis represents changes in (the orthogonal component of) capacity utilization. All growth rates are annual, and the sample period ranges from July 1967 to July 2015.

OA.3 Additional empirical results

OA.3.1 Non-linear exposures to aggregate productivity

In this section we consider whether nonlinear exposure to aggregate productivity can explain the utilization premium. Accounting for this type of nonlinearity is important if, for example, each utilization-sorted portfolio's exposure to aggregate shocks varies over time in a way that is correlated with the business cycle (as in the economic model for the utilization premium we present in Section 3). To examine whether these higher-order exposures to aggregate productivity explain the utilization premium we augment equation (2) with a quadratic aggregate productivity term and estimate the following regression:

$$Ret^e_{i,t} = \beta_{0,i} + \beta_{1,i}\text{Agg-Prod}_t + \beta_{2,i}\text{Agg-Prod}^2_t + \varepsilon_{i,t}. \tag{27}$$

Here, $Ret^e_{i,t}$ is the value-weighted excess return of the portfolio of interest, Agg-Prod_t is a proxy for aggregate productivity, and $\beta_{1,i}$ ($\beta_{2,i}$) captures the exposure of portfolio i to the linear (quadratic) effect of aggregate productivity. To implement this analysis we consider three different proxies for aggregate productivity: (i) the market return, (ii) utilization-adjusted TFP growth from Fernald (2012), and (iii) labor productivity from the Bureau of Labor Statistics (BLS). We also combine the slope coefficients on the linear and quadratic terms to form the (total) productivity beta of portfolio i (denoted by $\beta_{i,prod}$) as follows:

$$\beta_{i,prod} = \text{E}\left[\frac{\partial Ret^e_i}{\partial \text{Agg-Prod}}\right] = \beta_{1,i} + 2\beta_{2,i}\text{E}\left[\text{Agg-Prod}\right], \tag{28}$$

and compute the standard errors associated with $\beta_{i,prod}$ using the Delta method. We report the results of this analysis in Table OA.3.4.

Table OA.3.4: **Exposure of CU-sorted portfolios to aggregate productivity proxies**

	Market returns		Util.-adjusted TFP		Labor productivity	
Portfolio	β_{prod}	$t(\beta_{prod})$	β_{prod}	$t(\beta_{prod})$	β_{prod}	$t(\beta_{prod})$
Low (L)	1.37	(9.12)	1.18	(2.78)	0.88	(1.81)
Medium	1.25	(11.12)	0.76	(2.27)	0.54	(1.33)
High (H)	1.07	(6.53)	0.78	(2.02)	0.54	(1.18)
Spread (L-H)	0.30	(3.53)	0.40	(1.91)	0.34	(1.94)
Intercept	1.27	(0.41)	4.46	(1.33)	3.08	(0.99)

The table reports the exposures of portfolios sorted on capacity utilization to three different aggregate productivity proxies. The regression we estimate is: $Ret^e_{i,t} = \beta_{0,i}+\beta_{1,i}\text{Agg-Prod}_t+\beta_{2,i}\text{Agg-Prod}^2_t+\varepsilon_{i,t}$, where $Ret^e_{i,t}$ is the value-weighted excess return of portfolio i, Agg-Proxy is a proxy of aggregate productivity, and β_1 (β_2) is the sensitivity of portfolio i's excess return to the linear (quadratic) aggregate productivity term. We combine the linear and quadratic sensitivities to form the productivity beta (β_{prod}) following equation (28), and report β_{prod} in the table. Here, Agg-Proxy is either (i) excess market returns, (ii) utilization-adjusted TFP growth from Fernald (2012), or (iii) labor productivity growth from the BLS. Monthly returns are aggregated to the quarterly frequency so that each regression is estimated using quarterly data. Newey and West (1987) t-statistics associated with each exposure are reported in parentheses, with the standard errors associated with β_{prod} computed using the delta method. "Intercept" refers to the annualized value of β_0 (obtained by multiplying β_0 by four) from projecting the utilization spread on each productivity proxy. Finally, the sample spans July 1967 to December 2015.

Comparing Table OA.3.4, which features a non-linear relation to aggregate productivity, to Table 2, which features only a linear relation, delivers three key takeaways. First, accounting for the non-linear term, the low utilization portfolio's exposure to aggregate productivity remains significantly larger than the high utilization portfolio's exposure to productivity. Second, with non-linear exposures to aggregate productivity, the differences in productivity betas (L-H) in Table OA.3.4 are at least as large, if not larger, than those reported in Table 2. Third, when we measure aggregate productivity using excess market returns, the economic magnitude of the non-linear-CAPM alpha (intercept) in Table OA.3.4 falls to 1.27% per annum and becomes statistically insignificant with a t-statistic of 0.41. Likewise, the intercept from projecting the utilization premium on utilization-adjusted TFP growth from Fernald (2012) becomes statistically insignificant.

Motivated by this evidence, our theoretical model in Section 3 features only a single source of risk (aggregate productivity).

OA.3.2 Independence from value and investment effects

In this section we conditionally sort the sample of industries into portfolios along two dimensions. The first dimension corresponds to either the book-to-market ratio or investment rate, while the second dimension reflects the capacity utilization rate. This methodology allows us to examine the magnitude of the capacity utilization spread while controlling for either the value or the investment premium. We focus on book-to-market ratios and investment rates as these are the only two characteristics in Panel B of Table 3 that are significantly different between the two extreme capacity utilization portfolios and also command a risk premium that is aligned with the utilization spread. Below, we describe the portfolio formation procedure used to undertake this analysis.

Since our cross-section of 45 industries is too narrow to perform double sorts at the industry-level, we perform double sorts at the firm-level. To facilitate this firm-level analysis we need to assign each firm a capacity utilization rate that corresponds to the utilization rate of the industry to which the firm belongs. However, recall from Section OA.2 that our sample is comprised of overlapping industries that are defined with different degrees of granularity. This means that some firms may be matched to more than one industry in our sample. We execute the following matching algorithm to ensure that each firm is matched to the most granularly defined industry to which it belongs.

We start by assigning capacity utilization rates to all firms that belong to a six-digit NAICS code industry for which capacity utilization data is available. We then consider the five-digit NAICS code industries in our sample and identify the constituents of these industries that were not previously assigned a capacity utilization rate. These firms are then assigned a utilization rate corresponding to a five-digit NAICS code industry. This procedure then continues to the four-, three-, and two-digit NAICS code industries, in that order. If a previously unmatched firm belongs to two or more N-digit NAICS code industries, then we assign the firm the utilization rate of its "parent" (N-1)-digit NAICS code industry. Any firms unmatched at the end of this procedure are removed from the sample.

We then compute the book-to-market ratios and the investment rates of firm remaining in the sample using CRSP/Compustat data. Details on the construction of each variable are provided in Section OA.1 of the Online Appendix. We proceed with the bivariate sorting procedure, described below, once all data is computed and assigned to our sample of firms.

At the end of each June from 1967 to 2015 we first sort the cross-section of firms into three portfolios based on either their book-to-market ratios or investment rates. We use the 30^{th} and 70^{th} percentiles of the firm-level cross-sectional distribution of each characteristic to assign each firm to one of three portfolios. We ensure that any accounting data used to form portfolios in this first step has been publicly available for at least four months prior to its use. Next, within each of these three characteristic-sorted portfolios, we further sort firms into three additional portfolios on the basis of capacity utilization. We also use the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of capacity utilization rates in March of the same year to determine portfolio membership in this second step. This process produces nine portfolios that are each held from the beginning of July in year t to the end of June in year $t + 1$, at which point in time all portfolios are rebalanced.

Note that the portfolio breakpoints used in the bivariate sorting procedure described above (the 30^{th} and 70^{th} percentiles) differ from those used in our benchmark univariate sorting procedure described in Section 2.2 (the 10^{th} and 90^{th} percentiles). This modification is necessary to ensure that there is a sufficient number of firms in each of the nine doubles-sorted portfolios. The cost of these cruder breakpoints is that detecting a relation between capacity utilization and stocks returns after controlling for a potentially confounding characteristic, such as the investment rate, becomes relatively more difficult. It is also important to clarify that even though the second-stage sort is performed at the firm-level, the granularity of the data is still at the industry-level.

Table OA.3.5 reports the results of the bivariate portfolio sorts on the basis of both value- and equal-weighted portfolio returns. The rightmost column of each Panel shows the capacity utilization spread, along with its associated p-value, within portfolios that control for a characteristic of interest. Panels A and B report the results obtained by first controlling for book-to-market ratios, while Panels C and D report the results obtained by first controlling for investment rates. Finally, each Panel of the table also reports the p-value from a joint test on the null hypothesis that the capacity utilization spread across all three characteristic-sorted portfolios is zero.

The results show that after controlling for either book-to-market ratios or investment rate, the capacity utilization spread remains positive in 11 out of 12 cases. The utilization spread is also quantitatively large and statistically significant in most cases. Panel A shows that, keeping book-to-market ratios relatively constant, the equal-weighted capacity utilization spread is significantly different from zero at the 10% level within the low book-to-market portfolio and at the 5% level for both the medium and the high book-to-market portfolios. The joint p-value across the three spread portfolios is under 8%. The value-weighted returns reported in Panel B show that the capacity utilization spread is most pronounced among growth firms. Within this low book-to-market portfolio, the capacity utilization spread exceeds 6% per annum, an average return that is statistically significant at better than the 1% level. While the utilization spread remains positive and significant at the 10% level among medium book-to-market firms, the spread is statistically indistinguishable from zero within the portfolio of value firms. The p-value of 0.016 associated with the joint test in Panel B shows that the three value-weighted utilization spreads are statistically significant after conditioning on book-to-market.

Panels C and D show that, regardless of whether portfolio returns are value-weighted or equal-weighted, the capacity utilization spread typically exceeds 4% per annum within the portfolios of low and medium investment rate firms. In each of these cases the utilization spread is significantly different from zero at better than the 1% level. While the capacity utilization spread is not significant within the high investment rate portfolios, the joint test reported in each Panel is still rejected at the 5% level or better. Panel C (Panel D) shows that, conditioning on investment rates, the three equal-weighted (value-weighted) capacity utilization spreads are jointly and significantly different from zero at the 1% (5%) level.

Overall, the results in Table OA.3.5 suggest that neither the value nor the investment premium is driving the utilization spread. These results complement the Fama and MacBeth (1973) regressions in Section 2.6.

Table OA.3.5: **Controlling for book-to-market ratios and investment rates: double-sort analysis**

		Panel A: Capacity Utilization (EW)					Panel B: Capacity Utilization (VW)				
		Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)	Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)
Low (L)	BE/ME	9.40	8.10	6.26	3.14	(p=0.079)	11.63	10.53	5.55	6.08	(p=0.001)
Medium		16.92	13.36	12.82	4.10	(p=0.012)	13.29	10.45	11.01	2.27	(p=0.084)
High (H)		19.89	17.49	16.66	3.23	(p=0.039)	14.47	12.70	14.49	-0.02	(p=0.503)
					Joint test	(p=0.076)				Joint test	(p=0.016)

		Panel C: Capacity Utilization (EW)					Panel D: Capacity Utilization (VW)				
		Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)	Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)
Low (L)	I/K	20.06	17.74	12.62	7.44	($p < 0.001$)	15.52	11.30	10.55	4.97	(p=0.007)
Medium		17.07	13.65	13.08	3.99	(p=0.005)	13.35	10.64	9.07	4.28	(p=0.008)
High (H)		10.60	7.73	9.02	1.59	(p=0.249)	9.96	9.26	7.74	2.23	(p=0.180)
					Joint test	($p < 0.001$)				Joint test	(p=0.045)

The table reports portfolio returns obtained from conditional double-sort procedures, where the controlling variable (i.e., the first dimension sorting variable) is either a firm's book-to-market ratio or investment rate, and the second sorting variable is a firm's rate of capacity utilization. The sorting algorithm is as follows: First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of either the book-to-market ratio or the investment rate using the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of the characteristic of interest. Second, within each portfolio formed on the basis of the first sorting variable, we further sort firms into three additional portfolios on the basis of capacity utilization, using the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of capacity utilization rates in March of the same year. This process produces nine portfolios that are each held from the beginning of July in year t to the end of June in year $t+1$, at which point in time all portfolios are rebalanced. Portfolio returns are reported for both equal-weighted ("EW", Panels A and C) and value-weighted ("VW", Panels B and D) schemes. The rightmost column of each Panel shows the capacity utilization spread, along with its associated p-value, within portfolios that are first sorted on the controlling variable. These p-values are constructed using Newey and West (1987) standard errors. Each Panel also reports the p-value from a joint test on the null hypothesis that the capacity utilization spread across all three characteristic-sorted portfolios is zero. Panels A and B report the results obtained by first controlling for book-to-market ratios, while Panels C and D report the results obtained by first controlling for investment rates. The sample period is from July 1967 to December 2015.

OA.3.3 Independence from capital overhang

Aretz and Pope (2018) document that firms with higher capital overhang, or firms' whose installed productive capacities exceed their optimal amounts of capacity, have lower expected returns. The authors refer to these firms as possessing "capacity overhang." While Fama and MacBeth (1973) regressions in Section 2.6 show that the utilization premium and the overhang spread are empirically distinct, the conceptual similraity between these margins motivatues us to discuss how the notion of capacity utilization materially differs from that of capacity overhang. We also complement the regression analysis by showing that utilization and overhang each have a distinct impact on stock returns using portfolio double sorts.

Recalling equation (1), capacity utilization is defined as the ratio of a firm's actual output to its maximum potential output (its capacity). On the other hand, capacity overhang is the difference between a firm's *installed* capital stock and its *optimal* (value maximizing) level of capital. Intuitively, capacity utilization and capacity overhang are negatively related since a firm that desires to downscale can reduce its output by lowering the utilization of its existing capital. At the same time, the level of the firm's optimal capital stock also drops. If capital adjustments are not frictionless, then these frictions create a wedge between installed and optimal capacity, resulting in capacity overhang. Consequently, capacity utilization tends to decrease at the same time that overhang tends to increase.

The negative correlation between utilization and overhang is neither theoretically perfect nor empirically large in magnitude. Theoretically, the reason for this less than perfect correlation is that low capacity utilization is a result of a *costless and optimal* policy to keep some machines idle.[46] This optimal decision to reduce the utilization of capital does not hinge on any installation frictions or adjustment costs. In contrast, capacity overhang depends crucially on the degree to which investment is irreversible, as influenced by frictions such as convex adjustment costs. While low capacity utilization is optimal in states of low productivity, a non-zero amount of capacity overhang can never represent the first-best outcome for a firm. Consequently, capacity overhang should always be zero in a frictionless economy, whereas capacity utilization may still fluctuate depending on a firm's productivity.

While capacity overhang and capacity utilization are conceptually distinct, the rest of this section examines whether the two effects are also empirically distinct. Since Aretz and Pope (2018) document that high capacity overhang is associated with low expected returns there is no ex-ante reason to believe that the overhang effect is driving the capacity utilization spread. This is because low capacity utilization firms tend to have both high returns and high amounts of capacity overhang. Nonetheless, we perform portfolio double sorts to ensure that the capacity utilization spread is empirically separate from the overhang effect. We show that, controlling for capital adjustment frictions and the degree of irreversibility via the overhang measure of Aretz and Pope (2018), the capacity utilization spread survives. Moreover, controlling for the frictionless production decisions represented by capacity utilization, the overhang effect also survives.

To implement this analysis we construct a measure of firm-level capital overhang based on the statistical procedure described by Aretz and Pope (2018), summarized in Section OA.1 of

[46] Keeping machines idle in bad states is not only costless, but may also benefit the firm by preserving capital for future use in more productive states.

the Online Appendix. Following the discussion on the conceptual relation between capacity utilization and capacity overhang, Table OA.3.6 shows the correlation between overhang and utilization for each industry in our sample.[47] The magnitude of the correlation between the two variables decreases with the degree of aggregation. When we aggregate all firms in our sample, the correlation between capacity utilization and capacity overhang is negative, as expected, and amounts to -0.52. When we compute the correlation between these two variables on an industry-by-industry basis and average these pairwise correlations, the result is a modest average correlation of -0.32. The 95% confidence interval for this cross-sectional correlation shows a high degree of dispersion and ranges from -0.71 to 0.11. Panel C of this table reports that the average firm-level correlation drops to -0.11, and shows that this correlation becomes even more dispersed in the cross-section of firms. These results collectively highlight the fact that while capacity utilization and overhang are conceptually negatively related, the empirical correlation between these two variables is low.

Table OA.3.7 reports the results of performing portfolio double sorts along the dimensions of capacity utilization and capacity overhang using a firm-level analysis as described in Section OA.3.2. Panel A shows the average annual capacity utilization spread within three capacity overhang sorted portfolios when all returns are equal-weighted. The capacity utilization spread is positive and statistically significant within each overhang portfolio. The utilization spread is also jointly significant across all three overhang portfolios. Panel B shows that the results are similar when returns are value-weighted. Panels C and D report that the results are largely similar after changing the order of the sorts. Controlling for capacity utilization, the joint tests in Panels C and D show that the capacity overhang spread is positive and statistically significant on an equal-weighted basis, but is insignificant on a value-weighted basis.

[47]The industry-level capacity overhang measure is obtained by computing the average overhang for all firms that belong to each industry at each point in time. We also note that our sample is only comprised of manufacturing, mining, and utilities firms, whereas the sample of Aretz and Pope (2018) includes the entire Compustat universe, excluding financial firms and utilities.

Table OA.3.6: **Correlation between capacity utilization and capacity overhang**

Panel A: Correlation by Industry

Industry name	Sector	$\rho_{CU,OVER}$
Food, beverage, and tobacco	ND	-0.741
Printing and related support activities	ND	-0.728
Textile mills	ND	-0.690
Wood product	D	-0.687
Textiles and products	ND	-0.683
Beverage and tobacco product	ND	-0.642
Textile product mills	ND	-0.543
Computer and electronic product	D	-0.537
Food	ND	-0.534
Machinery	D	-0.528
Nonmetallic mineral product	D	-0.502
Support activities for mining	MU	-0.500
Coal mining	MU	-0.472
Computers, communications eq., and semiconductors	D	-0.469
Metal ore mining	MU	-0.450
Communications equipment	D	-0.392
Paper	ND	-0.366
Mining	MU	-0.348
Leather and allied product	ND	-0.345
Transportation equipment	D	-0.342
Mining (except oil and gas)	MU	-0.342
Semiconductor and other electronic component	D	-0.329
Automobile and light duty motor vehicle	D	-0.310
Motor vehicles and parts	D	-0.300
Primary metal	D	-0.254
Artificial and synthetic fibers and filaments	ND	-0.250
Chemical	ND	-0.248
Fabricated metal product	D	-0.214
Electrical equipment, appliance, and component	D	-0.195

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Table OA.3.6 – Continued from the previous page

Panel A: Correlation by Industry

Industry name	Sector	$\rho_{CU,OVER}$
Aerospace and miscellaneous transportation eq.	D	-0.183
Computer and peripheral equipment	D	-0.182
Apparel	ND	-0.170
Nonmetallic mineral mining and quarrying	MU	-0.144
Apparel and leather goods	ND	-0.140
Furniture and related product	D	-0.134
Plastics and rubber products	ND	-0.047
Plastics material and resin	ND	0.002
Iron and steel products	D	0.004
Petroleum and coal products	ND	0.071
Miscellaneous	D	0.083
Oil and gas extraction	MU	0.157
Synthetic rubber	ND	0.242

Panel B: Industry-level Summary Statistics

Statistic	Mean	Median	p5	p95
$\rho_{CU,OVER}$	-0.32	-0.34	-0.71	0.11

Pancel C: Firm-level Summary Statistics

$\rho_{CU,OVER}$	-0.11	-0.13	-0.66	0.51

Panel A shows the correlation between industry-level capacity utilization and industry-level capital overhang for each industry in the sample. Overhang at the industry level is computed as the simple average of firm-level overhang rates for all firms that belong to each industry. Panel B reports summary statistics for the industry-level correlations between capacity utilization and capacity overhang that are reported in Panel A. These summary statistics include the cross-sectional mean, median, 5th and 95th percentiles of the distribution of industry-level correlation coefficients. Panel C reports these same summary statistics for firm-level correlations between capacity utilization and capacity overhang.

Table OA.3.7: **Double-sorted portfolios: capacity utilization versus capacity overhang**

		Panel A: Capacity Utilization (EW)					Panel B: Capacity Utilization (VW)				
		Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)	Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)
Low (L)	Overhang	19.27	16.14	15.99	3.28	(p=0.026)	17.03	12.21	11.75	5.28	(p=0.025)
Medium		17.59	14.04	14.54	3.05	(p=0.023)	14.14	10.38	11.21	2.93	(p=0.059)
High (H)		14.10	10.29	8.78	5.32	(p=0.021)	12.84	10.83	7.90	4.94	(p=0.007)
					Joint test	(p=0.061)				Joint test	(p=0.079)
		Panel C: Overhang (EW)					Panel D: Overhang (VW)				
		Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)	Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)
Low (L)	CU	19.00	17.29	13.48	5.52	(p<0.001)	16.03	13.84	12.24	3.79	(p=0.050)
Medium		15.49	14.00	10.98	4.51	(p<0.001)	10.27	10.21	10.24	0.03	(p=0.494)
High (H)		16.31	13.55	9.07	7.23	(p<0.001)	12.29	10.35	8.87	3.42	(p=0.029)
					Joint test	(p<0.001)				Joint test	(p=0.153)

The table reports portfolio returns obtained from conditional double-sort procedures in which one sorting variable is capacity overhang and other sorting variable is capacity utilization. Two cases are considered: in Panels A and B the controlling variable (i.e., the first dimension sorting variable) is overhang, and the variable used in the second-stage sort is capacity utilization. In Panels C and D, the order is flipped: the first (second) stage sorting variable is capacity utilization (overhang). The sorting algorithm is as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of the first sorting variable, using the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of the variable of interest. Second, within each portfolio formed on the basis of the first sorting variable, we sort firms into three additional portfolios on the basis of the second sorting variable, using the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of the variable. This process produces nine portfolios that are each held from the beginning of July in year t to the end of June in year $t+1$, at which point in time all portfolios are rebalanced. Both equal-weighted ("EW", Panels A and C) and value-weighted ("VW", Panels B and D) portfolio returns are reported. The rightmost column of each Panel shows the spread on the basis of the second sorting variable, along with the p-value associated with null hypothesis this spread is zero. These p-values are constructed using Newey and West (1987) standard errors. Each Panel also reports the p-value from a joint test on the null hypothesis that the three spreads obtained by forming portfolios in the second stage are jointly equal to zero. The sample period is from July 1967 to December 2015.

OA.3.4 Dissecting the productivity spread

Imrohoroglu and Tuzel (2014) show that low productivity firms earn a high risk premium. While the results of Fama and MacBeth (1973) regressions reported in Table 5 show that productivity cannot explain the utilization premium, this section explores the opposite relation by examining whether capacity utilization can explain the productivity premium. We also examine the explanatory power of the component of productivity that is orthogonal to utilization. These analyses are motivated by the general form of a firm's production function:

$$Y = \underbrace{\text{Technology} \; \times \; \text{Markups} \; \times \; \text{Utilization}}_{\text{Total factor productivity (TFP)}} \cdot F(K, L), \tag{29}$$

where $F(\cdot)$ is a production function over capital (K) and labor (L). The residual obtained by projecting output on factor-share weighted capital and labor provides an estimate for TFP that can then be decomposed into three elements: technology shocks, time-varying markups, and time-varying capacity utilization. This decomposition of TFP motivates the empirical tests conducted below.

We begin by examining whether the TFP spread exists in our sample of manufacturing firms, mining firms, and utilities. This is necessary because our sample is relatively constrained compared to Imrohoroglu and Tuzel (2014) who examine the TFP spread in the entire Compustat universe, excluding financial and regulated firms. The results of replicating the TFP spread in our subsample of firms are reported in Panel A of Table OA.3.8. The equal-weighted TFP spread amount to 4.22% per annum and is statistically significant.[48]

Since capacity utilization is a fundamental component of TFP, we begin by examining whether the TFP spread survives controlling for capacity utilization. We conduct this analysis using a firm-level dependent double sort as described in Section OA.3.2. In other words, we construct the productivity spread within capacity utilization sorted portfolios. The results are reported in Panel B of Table OA.3.8 and show that the TFP spread is 4.56%, 4.21%, and 1.78% per annum within the portfolio of firms with low, medium, and high rates of capacity utilization, respectively. A joint test on the magnitude of the productivity premium across the three capacity utilization portfolios is statistically significant at the 5% level. This suggests that the productivity premium is distinct from the capacity utilization spread.

Next, we construct a measure for the technology and markup (TechMark) components of TFP by taking the difference between TFP and the capacity utilization rate, as motivated by equation (29).[49] This allows us to isolate the component of TFP that is distinct from capacity utilization and examine the relation between this orthogonal component and stock returns. We sort firms into portfolios based on the TechMark measure at the end of each June and report the results of these univariate sorts in Panel C of Table OA.3.8. The annualized spread between low and high TechMark firms is 3.29% and statistically significant.

Taken together, the results above indicate that the TFP premium is driven by two *distinct* underlying spreads: the TechMark and the capacity utilization spreads. Each of these spreads

[48]The value-weighted TFP spread is positive yet statistically insignificant using our subsample and time frame. For this reason we only focus on equal-weighted returns in this subsection.

[49]Additional details on the construction of this variable are available in Section OA.1 of the Online Appendix.

is statistically significant and economically large. We shed light on the contribution of each of these components to the overall productivity spread in Panel D of Table OA.3.8. This panel shows that the correlation between the TFP spread and the capacity utilization (TechMark) spread is 0.39 (0.96). In Table OA.3.9 we project the TFP spread on the utilization spread and find that the adjusted-R^2 is a modest 15%. When the TFP spread is projected on both the utilization spread and the TechMark spread, the adjusted-R^2 increases to 95% and the slope coefficient on the utilization spread remains statistically significant. This means that the majority of the time-series variation in the TFP spread appears to be driven by characteristics related to technology and markups rather than capacity utilization. Overall, this explains why the utilization spread survives controlling for TFP, and vice versa.

Table OA.3.8: **Dissecting the productivity spread**

Panel A: Univariate sorts on TFP				
	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low (L)	11.68	23.11	17.00	25.04
Medium	12.25	17.24	15.25	20.23
High (H)	11.16	16.18	12.78	20.73
Spread	0.51	13.79	4.22	12.23
(L-H)	(0.25)		(2.26)	

Panel B: TFP spread controlling for CU						
		TFP (EW)				
		Low (L)	Medium	High (H)	Spread(L-H)	p(Spread)
Low (L)	CU	19.24	17.09	14.68	4.56	(p=0.004)
Medium	CU	16.30	13.81	12.09	4.21	(p=0.007)
High (H)	CU	14.02	15.01	12.24	1.78	(p=0.143)
					Joint test	(p=0.031)

Panel C: Univariate sorts on TechMark				
	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low (L)	11.84	22.45	16.89	24.54
Medium	11.64	17.16	15.05	20.28
High (H)	11.66	16.17	13.60	20.91
Spread	0.18	12.90	3.29	11.52
(L-H)	(0.09)		(1.87)	

Panel D: Unconditional correlations		
ρ(CU,TFP)	ρ(CU,TechMark)	ρ(TFP,TechMark)
0.39	0.28	0.96

Panel A reports both the annual returns of value- and equal-weighted portfolios formed on total factor productivity (TFP), and the spread between low and high TFP (or productivity) portfolios. Mean (SD) refers to the average (standard deviation) of annual returns, and parentheses report Newey and West (1987) robust t-statistics. Panel B reports equal-weighted portfolio returns obtained from a double sort procedure in which firms are first sorted into three portfolios on the basis of capacity utilization (CU). Within each portfolio, firms are further sorted into three portfolios on the basis of TFP. The rightmost column of the panel show the p-value from a test on the null hypothesis that each TFP spread is zero, as well as a test on null hypothesis that the three spreads are jointly equal to zero. Panel C reports the annual returns of three portfolios sorted on the technology and markups (TechMark) component of TFP. In each of Panels A, B, and C, portfolio breakpoints are based on the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of the characteristic of interest. Panel D shows the pairwise correlations between equal-weighted univariate spreads formed on CU, TechMark, and TFP. The sample period is from July 1967 to June 2015, when the TFP data becomes unavailable. Additional details on the construction of each variable are provided in Section OA.1 of the Online Appendix.

Table OA.3.9: **Projections of the TFP spread on the utilization spread**

	(1)	(2)
β_0	2.50	0.41
	(1.49)	(0.98)
β_{CU}	4.34	1.43
	(8.99)	(6.38)
$\beta_{TFP^{\perp}}$		11.82
		(86.99)
$\bar{R}^2$	0.152	0.945

Panel A reports the slope coefficients from the following regression:

$$Spread_{TFP,t} = \beta_0 + \beta_{CU} Spread_{CU,t} + \varepsilon_{TFP,t},$$

where $Spread_{TFP,t}$ is the productivity spread and $Spread_{CU,t}$ is the utilization spread. Panel B report the coefficients of the following projection:

$$Spread_{TFP,t} = \beta_0 + \beta_{CU} Spread_{CU,t} + \beta_{TFP^{\perp}} Spread_{TechMark,t} + \varepsilon_{TFP,t},$$

where $Spread_{TechMark,t}$ is the Technology/markup spread. Portfolios are formed annually, at the end of each June, following our benchmark portfolio formation procedure, and returns range from July 1967 to June 2015. t-statistics, reported in parentheses, are computed using Newey and West (1987) standard errors.

OA.3.5 Methodological variations in portfolio formation

In this section we show that the capacity utilization spread is also robust to several implementation choices related to the portfolio formation procedure described in Section 2.2.

Variation in breakpoints. In the benchmark analysis we use the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of capacity utilization rates as breakpoints for the low and high utilization portfolios. Here, we modify these breakpoints and sort industries into quintiles instead. This choice of breakpoints doubles the number of industries in each of the extreme capacity utilization portfolios and ensures that the spread is not driven by idiosyncratic factors that may be at work when fewer industries populate the extreme portfolios. The value- and equal-weighted returns of these five portfolios are reported in Table OA.3.10. Despite using coarser breakpoints to form the portfolios, the value-weighted utilization spread is close to 5% per annum and statistically significant. This spread is less than 1% smaller in magnitude than the benchmark spread reported in Table 1. Portfolio returns also tend to decrease as the average utilization rate of each portfolio increases, with the equal-weighted returns monotonically decreasing in average utilization.

Variation in the sample period. While our sample period spans July 1967 to December 2015, we consider the impact of breaking the sample in half and examining the utilization spread in the most recent subsample that starts in July 1991. This subsample analysis is reported in Table OA.3.11 and shows that the magnitude of the spread is larger in the recent subsample than it is over the entire sample period. While the value-weighted spread has a mean return of 5.67% per annum between July 1967 and December 2015, its mean return between July 1991 and December 2015 is 9.09% per annum. As the second half of the sample is populated by two major recessions, the recession of the early 2000s and the Great Recession, this result also shows that the utilization spread is largely countercyclical.

Variation in the sample of industries. Our benchmark results are based on a cross-section of 45 industries. However, as explained in Section OA.2, some of these industries are comprised of firms that belong to multiple industries in the sample. To ensure that our results are not driven by this feature of the data, we repeat our baseline analysis using a subsample of industries whose constituent firms are distinct from one another. These 24 no-overlap industries are listed in Table OA.2.1 and the results of repeating our benchmark portfolio sorts in this subsample of industries are shown in Table OA.3.12. Within this subsample the value-weighted capacity utilization spread is to 6.65% per annum, and even larger than our benchmark spread of 5.7% per annum. Although we lose valuable statistical power by restricting the cross-section of industries, the value-weighted (equal-weighted) utilization spread is still statistically significant at the 5% (10%) level.

Importance of conditional sorting. In untabulated results we demonstrate the importance of the *conditional* portfolio sorting procedure described in Section 2.2. Specifically, we consider an alternative procedure in which each industry is permanently assigned to the first portfolio it is sorted into. This *unconditional* portfolio sort leads to a capacity utilization spread that is both economically and statistically insignificant. This result highlights that there is a significant degree of conditional variation in industry-level capacity utilization rates, and that this variation is important for generating the capacity utilization spread.

Table OA.3.10: **Capacity utilization spread: results based on quintile portfolios**

	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low (L)	13.31	18.97	10.23	20.41
2	11.88	17.85	9.74	18.92
Medium	8.78	18.60	7.68	18.57
4	9.25	18.09	7.51	17.52
High (H)	8.44	17.79	5.87	18.64
Spread	4.87	14.07	4.35	11.80
(L-H)	(2.35)		(2.57)	

The table reports annual returns of five portfolios sorted on the basis of capacity utilization, as well as the spread between the low (L) and the high (H) capacity utilization portfolios. The construction of these portfolios is identical to the benchmark analysis, except that quintile breakpoints used to sort industries into portfolios. Mean refers to the average annual return and SD denotes the standard deviation of annual returns. Parentheses report t-statistics computed using Newey and West (1987) standard errors. The portfolios are formed at the end of each June from 1967 to 2015 and are rebalanced annually, with portfolio returns ranging from July 1967 to December 2015.

Table OA.3.11: **Capacity utilization spread: results based on the recent subsample**

	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low (L)	15.29	22.74	11.72	21.81
Medium	10.04	16.95	8.24	16.86
High (H)	6.20	20.49	4.39	20.40
Spread	9.09	20.66	7.34	17.53
(L-H)	(2.39)		(2.22)	

The table reports annual returns of portfolios sorted on the basis of capacity utilization, as well as the spread between the low (L) and high (H) capacity utilization portfolios. The construction of the portfolios is identical to the benchmark analysis, except that the sample period only includes the recent period from July 1991 to December 2015. Mean refers to the average annual return and SD denotes the standard deviation of annual returns. Parentheses report t-statistics computed using Newey and West (1987) standard errors. The portfolios are formed at the end of each June from 1991 to 2015 and are rebalanced annually.

Table OA.3.12: **Capacity utilization spread: results based on non-overlapping industries**

Portfolio	Value-weighted Mean	Value-weighted SD	Equal-weighted Mean	Equal-weighted SD
Low (L)	15.43	20.56	11.52	20.25
Medium	10.36	16.70	7.94	18.17
High (H)	8.77	20.24	7.08	20.30
Spread	6.65	18.32	4.45	17.40
(L-H)	(2.51)		(1.77)	

The table reports annual returns of five portfolios sorted on the basis of capacity utilization, as well as the spread between the low (L) and high (H) capacity utilization portfolios. The construction of the portfolios is identical to the benchmark analysis, except that the sample of industries is restricted to those industries whose constituents do not belong to multiple industries in the sample (see Table OA.2.1, Column 3, for the list of these non-overlapping industries). Mean refers to the average annual return, SD denotes the standard deviation of annual returns. Parentheses report t-statistics computed using Newey and West (1987) standard errors. The portfolios are formed at the end of each June from 1967 to 2015 and are rebalanced annually, with portfolio returns spanning July 1967 to December 2015.

OA.3.6 Supplemental tables

Table OA.3.13: **Transition matrix of constituents between capacity utilization portfolios**

Portfolio in year t	Portfolio in year $t+1$: Low	Medium	High
Low	0.746	0.254	0.000
Medium	0.033	0.939	0.027
High	0.011	0.232	0.758

The table shows the probability of an industry sorted into portfolio $i \in$ {Low, Medium, High} in year t, where i is the row index, being sorted into portfolio $j \in$ {Low, Medium, High} in year $t+1$, where j is the column index. The transition probabilities are computed using annual capacity utilization data from June 1967 to December 2015. Industries are sorted into portfolios at the end of each June following the portfolio formation procedure described in Section 2.2.

Table OA.3.14: **Value-weighted capacity utilization spread and factor models**

	(1)	(2)	(3)	(4)
MKTRF	0.175	0.148	0.189	0.165
	(2.72)	(2.48)	(2.78)	(2.59)
SMB	0.155	0.153	0.069	0.039
	(1.94)	(1.88)	(0.70)	(0.45)
HML	0.074	0.022	-0.075	
	(0.66)	(0.21)	(-0.46)	
UMD		-0.144		
		(-1.76)		
RMW			-0.241	
			(-1.55)	
CMA			0.294	
			(1.17)	
I/A				0.279
				(1.73)
ROE				-0.411
				(-3.01)
α	4.013	5.578	4.235	5.892
	(1.61)	(2.24)	(1.60)	(2.26)
R^2	0.033	0.045	0.047	0.072

The table reports the results of time-series regressions of the value-weighted capacity utilization spread (the portfolio that buys low capacity utilization industries and shorts high capacity utilization industries) on a number of common risk factors. Parameter estimates are obtained by regressing monthly excess returns on each set of monthly risk factors. Each reported α is annualized by multiplying the equivalent monthly coefficient by 12. MKTRF is the excess return of the market portfolio. SMB and HML are the size and value factors of the Fama and French (1993) three-factor model, while MOM is the momentum factor of Carhart (1997). RMW and CMA correspond to the profitability and investment factors of the Fama and French (2015) five-factor model. Finally, I/A and ROE denote the investment and profitability factor in the Hou et al. (2015) q-factor model. t-statistics are computed using Newey and West (1987) standard errors and are reported in parentheses. Returns span July 1967 to December 2015.

OA.4 Additional theoretical results

OA.4.1 Model-implied double sort on book-to-market

This section reports the results of a conditional double sort of model-implied stock returns on book-to-market ratios and capacity utilization rates. The portfolio formation procedure follows the discussion in Section 4.1. The results of the analysis are reported in Table OA.4.15 and show that the utilization premium also exists *within* book-to-market portfolios. The section also discusses the rationale for why our model, which features a single aggregate shock, produces a spread along these two separate dimensions.

Table OA.4.15: **Conditional Double-sort in the model**

	Low CU	Medium CU	High CU	Spread (L-H)
Low B/M	12.20	11.60	9.29	2.91
Medium B/M	12.30	11.19	8.44	3.86
High B/M	11.83	9.99	9.66	2.17

The table shows the model-implied equal-weighted returns obtained from a conditional double-sort procedure in which the control variable (i.e., the first dimension sorting variable) is the book-to-marke ratio and the second dimension sort variable is the capacity utilization rate. The portfolios are constructed as follows. First, in each period firms are sorted into three portfolios based on the cross-section of book-to-market ratios from period $t-1$ using the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of book-to-market ratios. Next, within each book-to-market portfolio, firms are further sorted into three additional portfolios on the basis of capacity utilization in period $t-1$ using the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of capacity utilization rates. This procedure produces nine portfolios that are held for one period, and are then rebalanced. The table also shows the capacity utilization spread associated with each book-to-market portfolio. Here, model implied moments are based on one simulation of the model that features 1,000 firms and 40,000 periods (years.)

As shown in Table OA.4.15, the model can produce the utilization premium *within* book-to-market portfolios. There are two reasons why our single-shock model is capable of simultaneously generating a spread along these two separate dimensions. First, despite the comovement between investment, utilization and book-to-market in the model (all relate to Tobin's q), the correlation between the latter two margins is less than perfect. Our model features a real option that induces "wait and see" periods of investment inaction. In these periods utilization and investment do not comove, as utilization substitutes exercising the costly option to disinvest capital. Second, while both utilization and book-to-market are linked to the same aggregate shock, these relations to the aggregate shock are non linear.

This occurs, for example, because of time-varying betas and non-linear policy functions. Overall, the model produces enough dispersion in firm-level risk to conduct this double sort.

OA.4.2 Sensitivity of the model for risk premia

In this section we numerically illustrate the intuition for the utilization spread, discussed in Section 4.2. We show the sensitivity of the spread to ingredients (1)–(3) of our model (the quadratic capital adjustment cost, fixed cost of disinvestment, and countercyclical market price of risk, respectively). We also show that the utilization spread is largely unaffected by perturbing the parameters governing the evolution of aggregate productivity. The results of this analysis are presented in Table OA.4.16. The table reports the mean value-weighted of the utilization spread, along with the spread's exposure (β) to aggregate productivity (as measured by excess market returns).[50] The table also mean and volatility of the equity risk premium in the model under each alternative calibration.

The results in rows (2) and (3) show that when the extent of the first friction, the quadratic capital adjustment costs, is perturbed, the magnitudes of the utilization spread changes but β is largely unaffected. As this friction is increased in row (3), the magnitude of the utilization spread increases. With higher adjustment costs, firms can less readily alter the level of their capital stocks, and low utilization implies more underlying capital risk.

Row (4) considers an economy is which the second ingredient, the fixed cost of capital disinvestment, is removed but the remaining two frictions are held constant. The utilization spread still exists, although its magnitude is decreased by almost 1% per annum. The decrease in the utilization spread reflects how removing the fixed cost of disinvestment better allows firms to shed their capital stock instead of substituting disinvestment with temporary declines in utilization. However, the fact that the utilization spread remains sizable indicates that firms still cannot fully absorb productivity shocks into their capital stock.

Next, rows (5), (6), and (7) consider the role of the third ingredient, the countercyclical market price of risk. In particular, row (6) illustrates how a more countercyclical market price of risk translates into a higher equity risk premium and volatility of aggregate market returns, as well as an increased utilization spread. This occurs because the asymmetry between good and bad aggregate productivity is widened. Row (7) indicates that both the equity risk premium and capacity utilization spread are severely diminished with an acyclical market price of risk.

Rows (8) and (9) then show how the utilization spread changes as the persistence of

[50] Note that the utilization premium is *not* given by β times the market equity premium because the unconditional CAPM does not hold in the model, as betas are time-varying. Nonetheless, the correlation between β and the utilization premium is always positive.

aggregate productivity shocks changes. The results in row (8) show that when aggregate productivity is less persistent, the magnitude and the volatility of the equity risk premium decrease. Similarly, the mean utilization premium falls slightly, as does the utilization spread's exposure to aggregate productivity shocks. The opposite patterns emerge in row (9), when the persistence of aggregate productivity increases.

Finally, rows (10) and (11) of the table display how the utilization premium and equity risk premium both fall (rise) when aggregate productivity becomes less (more) volatile. The same patterns hold true for the volatility of the equity risk premium, and the exposure of the utilization premium to aggregate productivity shocks. Importantly, in rows (8)–(11), the model implied utilization premium changes by at most 0.6% in absolute value compared to the benchmark case, and falls within the empirical 95% confidence interval.

Table OA.4.16: **Model-implied capacity utilization spread across alternative calibrations of the model**

Row	Model	$E\left[R^M\right]$	$\sigma\left(R^M\right)$	$E\left[R^{CU}\right]$	β
	Baseline				
(1)		5.39	20.89	5.12	0.25
	Different ϕ				
(2)	Low ($\phi = 1.40$)	5.39	20.85	5.06	0.25
(3)	High ($\phi = 1.60$)	5.39	20.94	5.18	0.25
	No fixed cost				
(4)		5.72	20.39	4.53	0.22
	Different γ_1				
(5)	Low ($\gamma_1 = -8.60$)	5.26	20.48	5.06	0.24
(6)	High ($\gamma_1 = -9.00$)	5.52	21.31	5.18	0.26
(7)	Acyclical ($\gamma_1 = 0$)	1.88	9.94	2.68	0.02
	Different ρ_x				
(8)	Low ($\rho_x = 0.899$)	4.51	17.48	4.69	0.16
(9)	High ($\rho_x = 0.945$)	6.59	25.54	5.55	0.39
	Different σ_x				
(10)	Low ($\sigma_x = 0.0137$)	4.96	19.77	4.91	0.23
(11)	High ($\sigma_x = 0.0143$)	5.84	22.03	5.34	0.27

The table reports model-implied population moments under various calibrations. The table reports the equity premium ($E[R^M]$), the volatility of the market return ($\sigma\left(R^M\right)$), the level of the capacity utilization spread ($E[R^{CU}]$), and the capacity utilization spread's exposure to aggregate productivity (β), as measured by model-implied market returns. Each moment is reported as an annual percentage. and each alternative calibration is identical to the benchmark calibration in all ways except for altering the specified parameter of interests. The parameters altered are the fixed cost of disinvestment (f), the quadratic capital adjustment cost (ϕ), the cyclicality of the market price of risk (γ_1), the persistence of the aggregate productivity process (ρ_x), and the volatility of the aggregate productivity process (σ_x). To compute β in the model, the volatility of market returns is scaled to match the volatility of market returns in the data All moments are based on a simulations of 1,000 firms over 40,0000 periods (years).

OA.4.3 Discussion of the model's assumptions

The model assumes a countercyclical market price of risk to break the symmetry between high and low utilization firms in the presence of symmetric convex adjustment costs. While we do not micro found the cyclicality, it can arise in a general equilibrium setup by assuming habits preferences or time-varying volatility that is countercyclical (e.g., Campbell and Cochrane (1999) and Bansal and Yaron (2004)).[51]

Additionally, the model only features a real option to disinvest. While we could, in principle, also include a fixed cost for expanding capacity to the model, thereby making investment a real option, we refrain for doing so to keep the dimensionality of the model's parameters low. Since the prior literature emphasizes that the adjustment costs of disinvestment are larger than those of investment (e.g., Zhang (2005)), our model captures this notion in a parsimonious manner. Importantly, Section 5 shows that our model with flexible utilization produces a sizable dispersion in risk premia without relying on large adjustment frictions that distort firm-level investment dynamics (Clementi and Palazzo, 2019).

Motivated by the empirical evidence in Sections 2.4 and OA.3.1, our framework relies on exposures to a single priced state variable: productivity. Despite having only a single aggregate shock, the model-implied CAPM alpha can be non-zero in short sample simulations (but statistically indistinguishable from zero when considering a 95% confidence interval), and the correlation between utilization and investment (or book-to-market) is positive but smaller than one. The former happens because of cyclicality in risk exposures, and the latter happens as utilization can serve as a substitute for disinvestment in downturns.

While not necessary quantitatively, featuring additional sources of aggregate risk could reduce the model-implied correlation between the utilization premium and other spreads related to intensive-margin characteristics.

[51] Countercyclical risk premia are also common components of models related to other asset markets, such as the currency and fixed income markets (e.g., Bansal and Shaliastovich (2013) and Lustig, Roussanov, and Verdelhan (2014)).

OA.4.4 Supplemental tables and figures

Table OA.4.17: **Model-implied CAPM alpha**

Portfolio	$[R^{CU}]$	α_{CAPM}
Low (L)	9.01 [4.24,16.87]	0.36 [-1.69,2.55]
Medium	6.93 [3.14,14.07]	-1.24 [-1.81,-0.72]
High (H)	4.97 [-0.10,12.66]	-2.80 [-6.26,0.59]
Spread (L-H)	4.04 [0.38,8.75]	3.16 [-0.94,7.42]

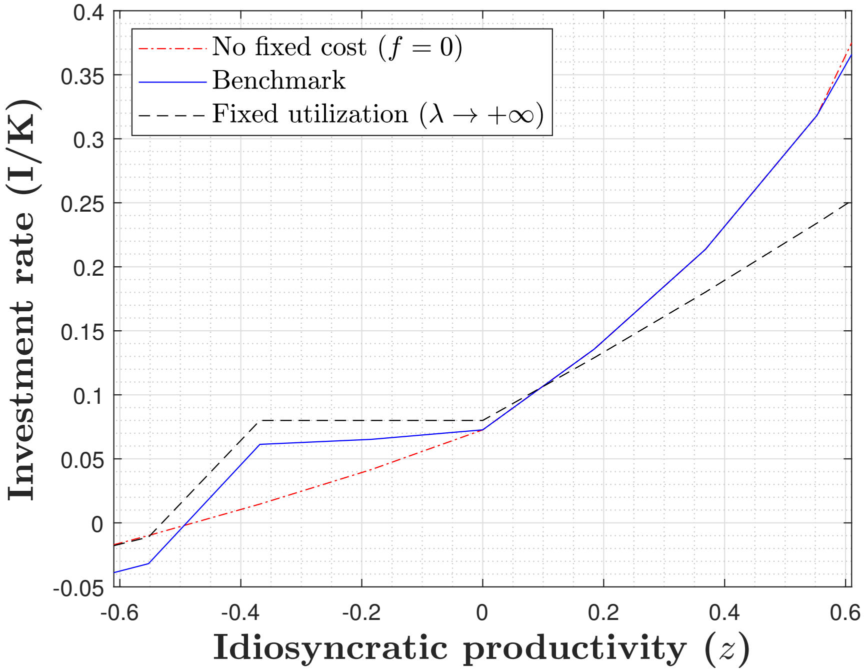
The table reports the average annual value-weighted returns and CAPM alphas (α_{CAPM}) of portfolios sorted on capacity utilization at the industry-level across short-sample simulations of our model economy. As in the empirical analysis, an industry is sorted into the high (low) utilization portfolio if its level of capacity utilization is above (below) the 90^{th} (10^{th}) percentile of the cross-sectional distribution of capacity utilization rates in the previous period. Industry-level returns are simulated using the procedure described in Section 4.1, and short-sample moments are obtained by averaging moments across 500 simulations of 50 industries for 50 periods (years). Finally, square brackets report the 95% confidence interval related to each moment across the 500 Monte Carlo simulations of the economy.

Table OA.4.18: **Capacity utilization spread: sensitivity to depreciation shocks**

	Positively correlated $\varepsilon^{\delta}_{i,t}$		Negatively correlated $\varepsilon^{\delta}_{i,t}$	
Portfolio	$E\left[R^{CU}\right]$	β	$E\left[R^{CU}\right]$	β
Low (L)	7.70	1.06	10.21	1.64
Medium	5.94	1.01	7.79	1.51
High (H)	4.38	0.96	5.74	1.38
Spread (L-H)	3.32	0.09	4.46	0.26

The table reports the average model-implied annual value-weighted returns of portfolios sorted on capacity utilization, as well as the exposure of each utilization portfolio to market returns (β), at the industry level. As in the empirical analysis, an industry is sorted into the high (low) utilization portfolio if its level of capacity utilization is above (below) the 90^{th} (10^{th}) percentile of the cross-sectional distribution of capacity utilization rates in the previous period. Here, the model economy is identical to the benchmark case and calibration with one exception: the depreciation rate of each firm is subject to an exogenous shock, as represented by equation (25) and described in Section 5.5. In the left (right) portion of the table these depreciation rate shocks are perfectly positively (negative) correlated with the aggregate productivity shocks. Industry-level returns are simulated using the procedure described in Section 4.1. Population moments are obtained from one simulation of 50 industries for 40,000 periods (years).

Figure OA.4.2: **Model-implied investment policy**



The figure shows the optimal investment rate policy (I/K) as a function of idiosyncratic productivity (z). Capital and aggregate productivity are set at their stochastic steady-state values, and we let z varying between two standard deviations of its mean value. We consider the I/K policy under three versions of our model: (1) The benchmark model (solid blue line), (2) the model without fixed costs (i.e., $f = 0$) (the dashed red line), and (3) the model with fixed utilization (i.e., $\lambda \to +\infty$).

OA.5 Numerical model solution

To solve the model numerically we use value function iteration. The value function and the optimal policies implied by the firm's maximization problem in equation (15) are solved on a grid in a discrete state space. The grid for capital stock, K, features 501 grid points, with the endpoints of the grid chosen to be nonbinding. The aggregate productivity process, x, and the idiosyncratic productivity process, z, are each driven by an independent and identically distributed (i.i.d.) normal distribution. While each of these state variables has continuous support in the model, each variable needs to be transformed into a finite number of states in order to implement the numerical solution algorithm. We use the method of Tauchen and Hussey (1991) to discretized the z process into 11 states. Because the method of Tauchen and Hussey (1991) does not work well for persistent processes, namely those with a persistence parameter greater than 0.90, we use the method of Rouwenhorst (1995) to discretize x into 5 states. Once the discrete state space has been constructed, conditional expectations are computed using matrix multiplication and the firm's maximization problem is solved using a global search routine. All results are robust to choosing finer grids.