Risk-Adjusted Capital Allocation and Misallocation*

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Abstract

We develop a theory linking "misallocation," i.e., dispersion in marginal products of capital (MPK), to systematic investment risks. Firms differ in their exposure to these risks, which we show leads naturally to heterogeneity in firm-level risk premia and, more importantly, MPK. Cross-sectional dispersion in MPK (i) depends on cross-sectional dispersion in risk exposures and (ii) fluctuates with the price of risk, and thus is countercyclical. We document strong empirical support for these predictions. We devise a strategy to quantify dispersion in risk exposures using data on expected stock market returns. Our estimates imply that risk considerations explain almost 40% of observed MPK dispersion among US firms and can rationalize a large persistent component in firm-level MPK. MPK dispersion induced by risk premium effects, although not *prima facie* inefficient, lowers the average level of aggregate productivity by as much as 7%, suggesting large "productivity costs" of business cycles.

JEL Classifications: D25, E32, G12, O47

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1 Introduction

A large and growing body of work has documented the "misallocation" of resources across firms, i.e., dispersion in the marginal product of inputs into production, and the resulting adverse effects on aggregate outcomes, such as productivity and output. Recent studies have found that even after accounting for a host of leading candidates – for example, adjustment costs, financial frictions or imperfect information – a substantial portion of observed misallocation seems to stem from other firm-specific factors, specifically, of a type that are orthogonal to firm fundamentals and are extremely persistent (if not permanent) to the firm.[1] Identifying exactly what – if any – underlying economic forces lead to this type of distortion has proven puzzling.

In this paper, we propose, empirically test and quantitatively evaluate just such a theory, linking capital misallocation to systematic investment risks. To the best of our knowledge, we are the first to make the connection between standard notions of the risk-return tradeoff and the resulting dispersion in the marginal product of capital (MPK). Indeed, our framework provides a natural way to translate the findings of the rich literature on cross-sectional asset pricing into the implications for the allocation of capital across firms. Further, we are able to quantify the effects of risk considerations – i.e., dispersion in risk premia and the extent of aggregate volatility (and so aggregate risk) – on macroeconomic outcomes, such as aggregate total factor productivity (TFP). Through the marginal product dispersion they induce, risk premium effects – though not *prima facie* inefficient – depress the achieved level of TFP, leading to a previously unexplored "productivity cost" of business cycles in the spirit of Lucas (1987).[2]

Our point of departure is a standard neoclassical model of firm investment in the face of both aggregate and idiosyncratic uncertainty. Firms discount future payoffs using a stochastic discount factor that is also a function of aggregate conditions. Critically, this setup implies that firms optimally equalize not necessarily MPK, but *expected, appropriately discounted*, MPK. With little more structure than this, the framework gives rise to an asset pricing equation governing the firm's expected MPK – firms with higher exposure to the aggregate risk factors require a higher risk premium on investments, which translates into a higher expected MPK. In fact, the model implies a beta pricing equation of exactly the same form that is often used to price the cross-section of stock market returns. The equation simply states that a firm's expected MPK should be linked to the exposure of its MPK to systematic risk (i.e., the firm's "beta"), and the "price" of that risk. This firm-specific risk premium appears exactly as what would otherwise be labeled a persistent distortion or "wedge" in the firm's investment decision.

The simple logic of the pricing equation contains substantial empirical content. Specifically,

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[1]See, e.g., David and Venkateswaran (2017). We discuss the literature in more detail below.

[2]Our analysis is also reminiscent of the approach in Alvarez and Jermann (2004), who use data on asset prices to measure the welfare costs of aggregate fluctuations.

we state and empirically investigate four key predictions – (i) exposure to standard risk factors priced in asset markets is an important determinant of expected MPK, (ii) movements in factor risk prices are linked to fluctuations in conditional expected MPK, (iii) MPK dispersion is positively related to beta dispersion and (iv) movements in factor risk prices are linked to fluctuations in MPK dispersion. We use a combination of firm-level production and stock market data to provide empirical support for these predictions. For example, (i) high MPK firms tend to offer high expected stock returns, suggesting that MPK is linked to exposure to systematic risk, and further, direct measures of these exposures are positively related to levels of MPK, (ii) common return predictors such as credit spreads and the aggregate price/dividend ratio predict fluctuations in mean firm-level MPK, (iii) in the cross-section, industries with higher dispersion in factor exposures, i.e., betas, have higher dispersion in MPK and (iv) both MPK dispersion and the return on a portfolio of high-minus-low MPK stocks contain predictable, and in fact countercyclical, components, as indicated by the same return predictors as in (ii).

After establishing these empirical results, we interpret them and gauge their magnitudes through the lens of a quantitative model. To that end, we enrich our theory by explicitly linking the sources of uncertainty to idiosyncratic and aggregate productivity risk.[3] We add two key elements to this framework – first, a stochastic discount factor designed to match standard asset pricing facts, as has become standard in the cross-sectional asset pricing literature (e.g., Zhang (2005) and Gomes and Schmid (2010)). Second, we allow for *ex-ante* cross-sectional heterogeneity in exposure, i.e., beta, with respect to the systematic productivity risk. In other words, the profitability (e.g., productivity or demand) of high beta firms is highly sensitive to the realization of aggregate productivity (which captures the state of the business cycle), low beta firms have low sensitivity, and indeed, the profitability of firms with negative beta may move countercyclically. The investment side of the model is analytically tractable and yields sharp characterizations of firm investment decisions and MPK.

This setup is consistent with the key empirical results described above, namely, firm-level expected MPKs depend on exposures to the aggregate productivity shock (the systemic risk factor in the economy) and due to the countercyclical nature of factor risk prices, are countercyclical, as is the cross-sectional dispersion in expected MPK. Further, we derive an expression for aggregate TFP, which is a strictly decreasing function of MPK dispersion. By inducing MPK dispersion, cross-sectional variation in factor risk exposures and a higher price of risk (which depends on the degree of aggregate volatility) reduce the long-run (average) level of achieved TFP. Thus, the model provides a novel, quantifiable link between financial market conditions, i.e., the nature of aggregate risk, and longer-run economic performance.

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[3]These can also be interpreted as shocks to demand. Later, we show that the environment can be extended to incorporate multiple risk factors and financial shocks.

The strength of these connections rely on three key parameters – the degree of heterogeneity in firm-level risk exposures and the magnitude and time-series variation in the price of risk. We devise an empirical strategy to identify these parameters using salient moments from firm-level and aggregate stock market data, specifically, (i) the cross-sectional dispersion in expected stock returns, (ii) the market equity premium and (iii) the market Sharpe ratio. We use a linearized version of our model to derive analytical expressions for these moments and show that they are tightly linked to the structural parameters. The latter two pin down the level and volatility of the price of risk and the first identifies the cross-sectional dispersion in firm-level risk exposures. Indeed, in some simple cases of our model, the dispersion in expected MPK coming from risk premium effects is directly proportional to the dispersion in expected stock returns – intuitively, both of these moments are determined by cross-sectional variation in betas.

Before quantitatively evaluating this mechanism, we add other investment frictions to the environment, specifically, capital adjustment costs. Although they do not change the main insights from our simpler model, we uncover an important interaction between these costs and risk premia – namely, adjustment costs amplify the effects of beta variation on MPK dispersion. Intuitively, beta dispersion leads to persistent differences in firm-level capital choices, even if those firms have the same average level of profitability. Adjustment costs further increase the dispersion in capital, which leads to even larger effects on MPK. On their own, adjustment costs do not lead to persistent dispersion in firm-level MPK, but they can augment the effects of other factors that do, such as the variation in risk premia we analyze here.

We apply our methodology to data on US firms from Compustat/CRSP and macro/financial aggregates, e.g., productivity and stock market returns. Our estimates reveal substantial variation in firm-level betas and a sizable price of risk – together, these imply a significant amount of risk-induced MPK dispersion. For example, our results suggest risk premium effects can explain as much as 38% of total observed MPK dispersion. Importantly, this dispersion is largely persistent – in other words, risk effects lead to persistent MPK deviations at the firm level, exactly of the type that compose a large portion of observed misallocation. Indeed, they can account for as much as 47% of this permanent component in the data. The implications of these findings for the long-run level of aggregate TFP are significant – cross-sectional variation in risk reduces TFP by as much as 7%. Note that this represents a quantitative estimate of the impact of the rich findings of the cross-sectional asset pricing literature on macroeconomic performance and further, a new connection between the nature of business cycle volatility and long-run outcomes in the spirit of Lucas (1987). Here, higher aggregate volatility leads to greater aggregate risk, increasing dispersion in required rates of return and MPK and thus reducing TFP. Our results suggest these "productivity costs" of business cycles may be substantial.

Our estimates also imply a significant countercyclical element in expected MPK disper-

sion. For example, our parameterized model produces a correlation between the cross-sectional variance in expected MPK and the state of the business cycle (measured by the aggregate productivity shock) of -0.31. To put this number in context, the correlation between MPK dispersion and aggregate productivity in the data is about -0.27. This result provides a risk-based explanation for the puzzling observation, made forcefully by Eisfeldt and Rampini (2006), that capital reallocation is procyclical, despite the apparently countercyclical gains – due to the countercyclical nature of factor risk prices and high beta of high MPK firms, such reallocation in downturns would require capital to flow to the riskiest of firms in the riskiest of times.

We pursue two important extensions of our baseline analysis. First, we add a flexible class of firm-specific "distortions" of the type that have been emphasized in the misallocation literature. These distortions can be fixed or time-varying and may be correlated or uncorrelated with firm-level characteristics (including betas) and with the state of the business cycle. We show that to a first-order approximation, our identification strategy and results are either unaffected by these distortions or are likely conservative (depending on the exact correlation structure of the distortions). These findings highlight an important feature of our empirical approach: although observed misallocation may stem from a variety of sources, our approach to measuring risk premium effects yields a robust estimate of the contribution of this one source alone. Second, we provide further, direct evidence on the extent of beta dispersion. Rather than relying on stock market data, we compute firm-level betas using production-side data by estimating time-series regressions of firm-level productivity on measures of aggregate productivity. The beta is the coefficient from this regression. This approach yields beta dispersion on par with the dispersion implied by the cross-section of stock market returns.

Why do firms (within an industry) have different exposure to the business cycle? Although our analysis does not require us to take a precise stand on this important question, we explore a number of potential explanations. First, we investigate the potential for heterogeneity in production technologies (i.e., input elasticities) and markups. We show that these types of heterogeneity can indeed lead to variation in firm responsiveness/exposure to shocks and so risk premia, but at most, are likely to account for about 12% and 6% of the estimated standard deviation of betas, respectively. Although non-negligible, these results suggest that the majority of beta dispersion stems from other sources. Next, we show that theories of "trading down" over the business cycle as in, e.g., Jaimovich et al. (2019), may be a promising explanation. In times of economic expansion, when purchasing power is high, consumers tend to substitute towards higher quality goods (e.g., expensive steak) while in downturns they substitute towards lower quality ones (e.g., McDonalds). This pattern makes higher quality products more procyclical and lower quality ones less so, or even countercyclical. Although systematically quantifying this channel across our full dataset is challenging (such an analysis would require comprehensive

product quality data), we provide more detailed evidence from a single industry where we were able to obtain a proxy for quality, namely average check per person across eating places. We show that low-price restaurants such as McDonalds and Burger King tend to have lower betas than high-price ones such as Ruth's Chris Steakhouse and further, average price and beta are positively related to expected returns and MPK. Although a case-study of one industry, these results highlight the main relationships implied by our theory and point to quality differentiation as a potentially important factor behind cross-firm beta dispersion.

Related Literature. Our paper relates to several branches of literature. First is the large body of work investigating resource misallocation, seminal examples of which include Hsieh and Klenow (2009) and Restuccia and Rogerson (2008). A number of papers have explored the role of particular factors in leading to misallocation, for example, Asker et al. (2014) capital adjustment costs, Midrigan and Xu (2014), Moll (2014) and Buera et al. (2011) financial frictions, Peters (2016), Edmond et al. (2018) and Haltiwanger et al. (2018) markup dispersion and David et al. (2016) information frictions.[4] Gopinath et al. (2017) and Kehrig and Vincent (2017) study the interactions of adjustment costs and financial frictions in explaining recent dynamics of misallocation in Spain and within firms, respectively. David and Venkateswaran (2017) provide an empirical methodology to disentangle various sources of capital misallocation and establish a large role for highly persistent firm-specific factors. Song and Wu (2015) also examine the contributions of multiple factors. We build on this literature by exploring the implications of a different dimension of financial markets for marginal product dispersion, namely, the risk-return tradeoff faced by risk-averse investors. In our theory, firm-level risk exposures manifest themselves as persistent firm-specific "wedges" of exactly the type found by David and Venkateswaran (2017). The addition of aggregate risk is a key innovation of our analysis – existing work has typically abstracted from this channel (either by assuming no aggregate uncertainty or risk-neutral agents). We show that the link between aggregate risk and observed misallocation is quite tight in the presence of heterogeneous exposures to that risk. Related to our work, Gilchrist et al. (2013) investigate and find a limited role for firm-specific borrowing costs. Where they focus mainly on costs of debt, we find a larger role for differences in costs of equity, which is an important source of financing for the firms in our data.[5] Indeed, in our simple theory, the Modigliani-Miller theorem holds, i.e., all firms are able to borrow at the common risk-free rate and thus there is no dispersion in borrowing costs. Yet equity costs – and so total costs of capital – may differ widely. One contribution of our work is extending the

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[4] Many papers study the role of firm-specific distortions, e.g., Bartelsman et al. (2013). Restuccia and Rogerson (2017), Hopenhayn (2014) and Eisfeldt and Shi (2018) provide excellent overviews of recent work on capital misallocation/reallocation.

[5] For example, the average leverage ratio in our sample is 0.28 (see Table 11).

insights in Gilchrist et al. (2013) to a broader notion of financing costs and showing that the implications for misallocation can be quite different.

Kehrig (2015) documents in detail the countercyclical nature of productivity dispersion. We build on this finding by relating fluctuations in MPK dispersion to time-series variation in the price of risk. A growing literature, starting with Eisfeldt and Rampini (2006), investigates the reasons underlying the observation that capital reallocation is procyclical. This indeed seems puzzling since, given higher cross-sectional dispersion in MPK in downturns, one should expect to see capital flowing to highly productive, high MPK firms in recessions. Our results bear on that observation by noting that the countercyclical nature of factor risk prices, in conjunction with heterogeneity in firm-level risk exposures, go some way toward reconciling this puzzle.

Our work exploits the insight, due to Cochrane (1991) and Restoy and Rockinger (1994), that stock returns and investment returns are closely linked (indeed, exactly coincide under constant returns to scale). Crucially for our purposes, investment returns are intimately linked with the marginal product of capital. Balvers et al. (2015) confirm the relationship under deviations from constant returns. In this context, our work is closely related to the growing literature that examines the cross-section of stock returns by viewing them from the perspective of investment returns, e.g., Zhang (2005), Gomes et al. (2006) and Liu et al. (2009), and forcefully summarized in Zhang (2017). This literature interprets common risk factors through firms' investment policies and shows that investment-based factors are priced in the cross-section of returns. Our objective is quite different and in some sense turns that logic on its head, in that we examine investment returns and the marginal product of capital as a manifestation of exposure to systematic risk, most readily measured through stock returns. Binsbergen and Opp (2017) also investigate the implications of asset market considerations for the real economic decisions of firms. They propose a framework where distortions in agents' subjective beliefs lead to "alphas," i.e., cross-sectional mispricings, and real efficiency losses, whereas we focus on the marginal product dispersion induced by heterogeneity in aggregate risk exposures. Our empirical work establishes a connection between marginal products and asset market outcomes and our quantitative work uses a workhorse macroeconomic model of firm dynamics augmented with risk-sensitive agents and aggregate risk to evaluate the implications of this insight. One of our key messages shares a common theme with this line of work – financial market considerations can have sizable effects on real outcomes by affecting capital allocation decisions.[6]

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[6]Relatedly, David et al. (2014) find that risk considerations play an important role in determining the allocation of capital across countries, i.e., can explain some portion of the "Lucas Paradox."

2 Motivation

In this section, we lay out a simple version of the standard, frictionless neoclassical theory of investment to motivate our empirical exercises. Section 4 enriches this environment for purposes of our quantitative work.

Firms produce output using capital and labor according to a Cobb-Douglas technology and face constant (or infinite) elasticity demand curves. Labor is chosen period-by-period in a spot market at a competitive wage. At the end of each period, firms choose investment in new capital, which becomes available for production in the following period so that $K_{it+1} = I_{it} + (1-\delta) K_{it}$, where δ is the rate of depreciation. Let $\Pi_{it} = \Pi_{it}(X_t, Z_{it}, K_{it})$ denote the operating profits of the firm – revenues net of labor costs – where X_t and Z_{it} denote aggregate and idiosyncratic shocks to firm profitability, respectively, and K_{it} the firm's level of capital. The analysis can accommodate a number of interpretations of the fundamental shocks, for example, as productivity or demand shifters. Given our assumptions, the profit function takes a Cobb-Douglas form, is homogeneous in K of degree $\theta < 1$ (due to curvature in production and/or demand) and is proportional to revenues. The marginal product of capital is equal to $MPK_{it} = \theta \frac{\Pi_{it}}{K_{it}}$. The payout of the firm in period t is equal to $D_{it} = \Pi_{it} - I_{it}$.

Firms discount future cash flows using a stochastic discount factor (SDF), M_{t+1}, which is correlated with the aggregate fundamental shock, X_t. We can write the firm's problem in recursive form as

$$V(X_t, Z_{it}, K_{it}) = \max_{K_{it+1}} \Pi_{it}(X_t, Z_{it}, K_{it}) - K_{it+1} + (1-\delta) K_{it} + \mathbb{E}_t[M_{t+1}V(X_{t+1}, Z_{it+1}, K_{it+1})] ,$$
(1)

where $\mathbb{E}_t[\cdot]$ denotes the firm's conditional expectations. The Euler equation is given by

$$1 = \mathbb{E}_t[M_{t+1}(MPK_{it+1} + 1 - \delta)] \quad \forall\ i, t .$$
(2)

MPK dispersion. An immediate consequence of expression (2) is that MPK (or even expected MPK) need not be equated across firms; rather, it is only appropriately discounted expected MPK that is equalized. To the extent that firms load differently on the SDF, their expected MPK will differ. Assuming a single source of aggregate risk for the sake of illustration, Appendix B derives the following factor model for expected MPK:[7]

$$\mathbb{E}_t[MPK_{it+1}] = \alpha_t + \beta_{it}\lambda_t .$$
(3)

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[7]It is straightforward to generalize to multi-factor environments, see, e.g., Appendix E.1.

Here, $\alpha_t = r_{ft} + \delta$ is the "risk-free" MPK (the user cost of capital), where r_{ft} is the (net) risk-free interest rate, $\beta_{it} \equiv -\frac{\text{cov}_t(M_{t+1}, MPK_{it+1})}{\text{var}_t(M_{t+1})}$ captures the exposure, or loading, of the firm's MPK on the SDF, i.e., the riskiness of the firm, and $\lambda_t \equiv \frac{\text{var}_t(M_{t+1})}{\mathbb{E}_t[M_{t+1}]}$ is the market price of that risk. In the language of asset pricing, the Euler equation gives rise to a conditional one-factor model for expected MPK. Expression (3) highlights that expected MPK is not necessarily common across firms and is a function of the risk-free rate of return, the firm's beta on the SDF, which may vary across firms, and the market price of risk. The cross-sectional variance of date t conditional expected MPK is then equal to

$$\sigma^2_{\mathbb{E}_t[MPK_{it+1}]} = \sigma^2_{\beta_t} \lambda^2_t \ , \tag{4}$$

where $\sigma^2_{\beta_t}$ is the cross-sectional variance of conditional betas. The extent to which risk considerations lead to dispersion in expected MPK depends on (i) the cross-sectional variation in firm-level risk exposures, i.e., beta and (ii) the price of risk. Further, given persistence in firm-level betas, the theory can clearly generate persistent differences in firm-level MPK, which are driven by the dispersion in required rates of return across firms.[8]

The strength of the mechanism linking dispersion in MPK to exposure to aggregate risk can be understood by inspection of expression (4) – predicted MPK dispersion is increasing in the dispersion in betas and also in the price of risk, λ. A key observation underlying our analysis is that asset pricing data suggest that risk prices are rather high. For example, a lower bound is given by the Sharpe ratio on the market portfolio, estimated to be around 0.5. However, even easily implementable trading strategies such as those based on value-growth portfolios or momentum, suggest numbers closer to 0.8, while hedge fund strategies report Sharpe ratios in excess of one. Taken at face value, these numbers suggest the possibility for substantial MPK dispersion – even in otherwise frictionless environments – after taking risk exposure in account.

Empirical Predictions. Even under the simple structure we have outlined thus far, the theory has a good deal of empirical content. Specifically, the expressions laid out above contain a number of both cross-sectional and time-series predictions:

1. *Exposure to standard risk factors is a determinant of expected MPK.* Expression (3) shows

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[8]To see this more clearly, we can take the unconditional expectation of equation (3) to obtain an approximate expression for the variance of mean MPK as $\sigma^2_{\mathbb{E}[MPK]} \approx \sigma^2_\beta \lambda^2$, where $\sigma^2_\beta \equiv \sigma^2_{\mathbb{E}[\beta_{it}]}$ denotes the variance of unconditional betas and $\lambda \equiv \mathbb{E}[\lambda_t]$ the unconditional expectation of the price of risk. The approximation is valid as long as $\text{cov}(\beta_i, \text{cov}(\beta_{it}, \lambda_t))$ is small. In line with the results in Lewellen and Nagel (2006), we find the time-series variation in betas to be quite modest. Further, they are persistent (for example, we find that CAPM betas have an implied one-year autocorrelation of 0.87). In the case of constant betas or if time variation in beta is orthogonal to variation in λ, the expression is exact.

that the same factors that determine the cross-section of asset returns – namely, exposure to the SDF – determine the cross-section of MPK. Firms with a higher loading on the SDF, i.e., higher beta, should have higher conditional expected MPK.

2. *Variation in the price of risk, λ_t, leads to predictable variation in mean expected MPK.* In particular, the mean conditional expected MPK should increase with the price of risk. This is the time-series implication of expression (3) – holding fixed the distribution of beta, movements in λ_t should positively affect the mean expected MPK. Since the price of risk is known to be countercyclical, this adds a countercyclical element to the mean conditional expected MPK.

3. *MPK dispersion is related to beta dispersion.* Expression (4) shows that variation in the cross-section of MPK is proportional to the variation in beta. Segments of the economy, for example, industries, with higher dispersion in beta should display higher dispersion in MPK.

4. *MPK dispersion is positively correlated with the price of risk.* Expression (4) links MPK dispersion to time-series variation in the price of risk. Given the dispersion in beta, when required compensation for bearing risk increases, MPK dispersion should increase as well.

Illustrative examples. Section 3 investigates each of these predictions in detail. Before doing so, however, it is useful to consider a number of more concrete illustrative examples (derivations for this section are in Appendix B).

Example 1: no aggregate risk (or risk neutrality). In the case of no aggregate risk, we have $\beta_{it} = 0 \ \forall \ i, t$, i.e., all shocks are idiosyncratic to the firm. Expressions (3) and (4) show that there will be no dispersion in expected MPK and for each firm, $\mathbb{E}_t \left[MPK_{it+1} \right] = r_f + \delta$, which is simply the riskless user cost of capital (which is constant in the absence of aggregate shocks). This is the standard result from the stationary models widely used in the misallocation literature where, without additional frictions, expected MPK should be equalized across firms.[9] This expression also holds in an environment with aggregate shocks but risk neutral preferences, which implies M_{t+1} is simply a constant (equal to the time discount factor).

Example 2: CAPM. In the CAPM, the SDF is linearly related to the market return, i.e., $M_{t+1} = a - b r_{mt+1}$ for some constants a and b. Because the market portfolio is itself an asset

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[9]With time-to build for capital and uncertainty over upcoming shocks there may still be dispersion in *realized* MPK, but not in *expected* terms, and so these forces do not lead to persistent firm-level MPK deviations.

with $\beta = 1$, it is straightforward to derive

$$\mathbb{E}_t\left[MPK_{it+1}\right] = \alpha_t + \underbrace{\frac{\text{cov}_t\left(r_{mt+1}, MPK_{it+1}\right)}{\text{var}_t\left(r_{mt+1}\right)}}_{\beta_{it}} \underbrace{\mathbb{E}_t\left[r_{mt+1} - r_{ft}\right]}_{\lambda_t},$$

i.e., expected MPK is determined by the covariance of the firm's MPK with the market return, which is the risk factor in this environment. The price of risk is equal to the expected excess return on the market portfolio, i.e., the equity premium.

Example 3: CCAPM. In the case that the utility function is CRRA with coefficient of relative risk aversion γ, standard approximation techniques give the pricing equation from the consumption capital asset pricing model:

$$\mathbb{E}_t\left[MPK_{it+1}\right] = \alpha_t + \underbrace{\frac{\text{cov}_t\left(\Delta c_{t+1}, MPK_{it+1}\right)}{\text{var}_t\left(\Delta c_{t+1}\right)}}_{\beta_{it}} \underbrace{\gamma \text{var}_t\left(\Delta c_{t+1}\right)}_{\lambda_t},$$

where Δc_{t+1} denotes log consumption growth. Expected MPK is determined by the covariance of the firm's MPK with consumption growth. The price of risk is the product of the coefficient of relative risk aversion and the conditional volatility of consumption growth.

3 Empirical Results

In this section, we investigate the empirical predictions outlined in Section 2.

Data. Our data come primarily from the Center for Research in Security Prices (CRSP) and Compustat.[10] We use data on nonfinancial firms with common equities listed on the NYSE, NASDAQ, or AMEX over the period 1965 to 2015. We supplement this panel with time-series data on market factors and aggregate conditions related to the price of risk. We use data on the Fama and French (1992) (Fama-French) factors, aggregate dividends and stock market values from Shiller (2005) and two measures of credit spreads: the Gilchrist and Zakrajsek (2012) (GZ) credit spread and the excess bond premium. We measure firm capital stock, K_{it}, as the (net of depreciation) value of property, plant and equipment (Compustat series PPENT) and firm revenue, Y_{it}, as reported sales (series SALE).[11] Ignoring constant terms, which will play no

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[10]By using Compustat data, our analysis focuses on large, publicly traded firms for which financial market data are available. Extending the analysis to private firms would be a valuable exercise, but faces a significant challenge in deriving accurate measures of risk premia (our alternative approach in Section 5.4 may be one way).

[11]Using book assets, a broader notion of firm capital, yields similar results.

role in our analysis, we measure the marginal product of capital (in logs, henceforth denoted with lowercase) as $mpk_{it} = y_{it} - k_{it}$.[12] Appendix A.1 provides further details on how we construct our dataset and the series that we use. We can now revisit the predictions from Section 2.

1. Exposure to standard risk factors is a determinant of expected MPK. We investigate this key implication of our framework in several ways.

Portfolio sorts.   First, we examine the relationship between MPK and stock market returns. To do so, we form MPK-sorted portfolios of firms. This approach follows widespread practice in empirical finance, which has generally moved from addressing variation in individual firm returns to returns on portfolios of firms, sorted by factors that are known to predict returns. In our setting, this procedure proves useful to eliminate firm-specific factors unrelated to MPK that may affect returns and so allows us to hone in on the predictability of excess returns by MPK. We sort firms into five portfolios based on their year t MPK, where portfolio 1 contains low MPK firms and portfolio 5 high MPK ones. The portfolios are rebalanced annually. We then compute the contemporaneous and one-period ahead equal-weighted excess stock return to each portfolio, denoted r_t^e and r_{t+1}^e, respectively.[13] We also compute the excess return on a high-minus-low MPK portfolio (MPK-HML), which is an annually rebalanced portfolio that is long on stocks in the highest MPK portfolio and short on stocks in the lowest.

The focus in the misallocation literature is generally on within-industry variation in MPK.[14] Thus, for completeness, we perform both industry and non industry-adjusted portfolio sorts. To control for industry effects, we demean firm-level *mpk* by industry-year and sort firms based on this de-meaned measure. Although much of our analysis will focus on the within-industry variation, the non-adjusted results are interesting in their own right (discussed more below) and confirm that the link between MPK and stock returns holds at various levels of aggregation.

We report the non industry-adjusted results in Panel A of Table 1. The table reveals a strong relationship between MPK and stock returns – high MPK portfolios tend to earn high excess returns. The first row shows that the difference in contemporaneous returns between high and low MPK firms, i.e., the excess return on the MPK-HML portfolio, is over 8% annually. The second row confirms that this finding does not simply result from the simultaneous response

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[12]In our setup, operating profits are proportional to revenues, making this a valid measure of the *mpk*.

[13]When computing future returns, we follow Fama and French (1992) and associate the MPK for fiscal year t with returns from July of year $t+1$ to June of year $t+2$. Value-weighted portfolios yield similar magnitudes, though the standard errors are greater in some specifications since value-weighting the smaller within-industry samples can increase the variance of portfolio returns. In our log-normal model below, equal-weighted dispersion will be the key object of interest.

[14]There may be heterogeneity across industries on a number of dimensions, for example, in production function coefficients or industry-level exposure to aggregate shocks.

of stock returns and MPK to the realization of unexpected shocks – one-period ahead excess returns are in fact predictable by MPK. The predictable spread on the MPK-HML portfolio is almost 5% annually. Both the contemporaneous and future MPK-HML spreads are statistically different from zero at the 99% level. Thus, high MPK tend to offer high stock returns, both in a realized and an expected sense, suggesting that MPK differences reflect exposure to risk factors for which investors demand compensation in the form of a higher rate of return.

Table 1: Excess Returns on MPK-Sorted Portfolios

Portfolio	Low	2	3	4	High	MPK-HML
	Panel A: Not Industry-Adjusted					
r^e_t	7.00**	9.08**	10.67***	12.00***	15.25***	8.25***
	(2.01)	(2.53)	(2.93)	(3.09)	(3.71)	(4.54)
r^e_{t+1}	8.60**	12.27***	13.48***	13.73***	13.48***	4.87***
	(2.48)	(3.47)	(3.80)	(3.62)	(3.36)	(2.81)
	Panel B: Industry-Adjusted					
r^e_t	6.98	8.91**	10.59***	12.28***	15.78***	8.80***
	(1.63)	(2.52)	(3.05)	(3.30)	(3.73)	(9.54)
r^e_{t+1}	11.10***	11.55***	12.71***	12.70***	13.69***	2.59***
	(2.61)	(3.35)	(3.75)	(3.50)	(3.36)	(2.98)

Notes: This table reports stock market returns for portfolios sorted by *mpk*. r^e_t denotes equal-weighted contemporaneous annualized monthly excess stock returns (over the risk-free rate) measured in the year of the portfolio formation from January to December of year t. r^e_{t+1} denotes the analogous future returns, measured from July of year $t + 1$ to June of year $t + 2$. Industry adjustment is done by de-meaning *mpk* by industry-year and sorting portfolios on de-meaned *mpk*, where industries are defined at the 4-digit SIC code level. t-statistics in parentheses, computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel B of Table 1 reports the within-industry results. The relationship between MPK and stock returns remains strong even when comparing across firms within a particular industry – the MPK-HML contemporaneous excess return remains over 8% annually and the future excess return is over 2.5%. Both are statistically significant at the 99% level. Thus, a large component of the return spread predictable by MPK remains after controlling for industry-level heterogeneity.[15] Comparing the two panels reveals that there is indeed an industry-level component of excess returns that is predictable by an industry-level component of MPK. Although we do not explore this finding in much more detail in this paper, it is reassuring confirmation of the link we are after – firms in industries with high average MPK tend to offer higher returns (in a predictable sense) than firms in low MPK industries, suggesting that

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[15]Although there are several measurement differences, the results in Table 1 are related to the "profitability premium" documented in Novy-Marx (2013) and others, i.e., high profit-to-capital firms earn high excess returns (both industry and non industry-adjusted). Further, Novy-Marx (2013) finds that the sales-to-assets component of profitability is the most directly related to higher returns (Appendix A.2 in that paper).

industry-level exposures to aggregate risk factors may be important as well.

In Appendix I.1, we explore a number of variants of Table 1. For example, we expand the number of portfolios, examine measures of unlevered returns and consider longer-horizon future returns. The relationship between MPK and stock returns continues to hold under all these alternatives. We perform double-sorts on size and book-to-market and verify that the return spreads based on MPK are not fully explained by the latter two factors (although they are both correlated with MPK). We also present summary statistics of the portfolios across a number of characteristics and consider several additional measurement issues (for example, we show that the results are unlikely to be driven by unmeasured intangible capital).

Measures of risk exposures and expected MPK. The second way we verify prediction 1 is to directly relate firm MPK to measures of risk exposures. To do so, we estimate regressions of the form

$$mpk_{it+1} = \psi_0 + \psi_\beta \beta_{it} + \zeta_{it+1} , \tag{5}$$

where β_{it} is a measure of firm i exposure to aggregate risk at time t. The specification tests whether observable measures of firm-level risk exposures are indeed correlated with higher MPK. We estimate (5) at an annual frequency and lag the right-hand side variable to control for the simultaneous effect of unexpected shocks on contemporaneous measures of beta and MPK. We construct four different measures of these exposures. First, we compute standard CAPM and Fama-French stock market betas (β_{CAPM} and β_{FF}, respectively) by estimating firm-level regressions of stock returns on the risk factors from each of these models. In the CAPM, the single risk factor is the aggregate market return. The three Fama-French factors are the market return, the return on a portfolio that is long in small firms and short in large ones (SMB), which captures the size premium and the return on a portfolio that is long in high book-to-market firms and short in low ones (HML), which captures the value premium. In each model, the coefficient on the risk factor(s) yields a measure of beta. To obtain a single measure of risk exposure in the multi-factor Fama-French model, we combine the estimated betas into a single value using estimated prices of risk from Fama and MacBeth (1973) regressions. We provide details of these calculations in Appendix A.1.

With these measures in hand, we are in a position to estimate equation (5). We report the results in columns (1)-(2) in Table 2. Both measures have significant explanatory power for subsequent MPK. For example, the estimate in column (1) implies that each unit increase in the CAPM beta is associated with a 20% increase in expected MPK.[16]

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[16]We report two-way clustered standard errors by firm and industry-year to allow for arbitrary time-series correlations for a given firm and for correlations across firms within an industry at a particular time. These standard errors do not account for the error associated with the generated regressors (betas). As in

Table 2: Predictive Regressions of MPK on Aggregate Risk Exposures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{CAPM}	0.209***				0.014**			
	(12.65)				(2.13)			
β_{FF}		0.068***				0.005***		
		(15.11)				(2.88)		
$\beta_{CAPM,MPK}$			0.065***				0.024***	
			(5.46)				(3.80)	
$\beta_{FF,MPK}$				4.005***				1.097***
				(9.49)				(4.68)
Observations	105404	104702	79404	78920	97566	96923	72477	71990
R^2	0.025	0.037	0.003	0.009	0.059	0.060	0.065	0.066
F.E.	No	No	No	No	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	Yes	Yes	Yes

Notes: This table reports the results of a panel regression of year-ahead *mpk* regressed on measures of firm exposure to aggregate risk. Each observation is a firm-year. The dataset contains approximately 10,000 unique firms. F.E. denotes the presence of industry-year fixed effects. Standard errors are two-way clustered by firm and industry-year. *t*-statistics in parentheses. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Both of these measures of firm-level risk exposures are based only on stock market data. Although our theory implies these should be related to MPK (and they have a rich tradition in asset pricing), expression (3) suggests that we look directly at the exposure of firm-level MPK to aggregate risk factors. To do so, we perform the same two exercises just described, but instead using firm-level MPK – namely, we regress *mpk* on the market return and Fama-French factors to obtain two direct measures of MPK exposure to aggregate risk ($\beta_{CAPM,MPK}$ and $\beta_{FF,MPK}$) and estimate specification (5) using these measures as the predictive variable. We report the results in columns (3) and (4) of Table 2. The table shows that, similar to stock market betas, firm-level "MPK betas" are significant predictors of future firm MPK. In sum, our findings in Table 2 confirm a key implication of expression (3): firm-level risk exposures – measured using stock market or MPK exposures – are significant determinants of firm-level expected MPK.

In columns (5)-(8) of Table 2, we estimate analogous regressions with the addition of industry-year fixed-effects and a set of standard firm-level controls, namely, market capitalization, book-to-market ratio, profitability, and market leverage.[17] All of the beta coefficients remain positive and statistically significant.

Guren, McKay, Nakamura, and Steinsson (2018), this requires a bootstrap procedure that clusters only on time but precludes clustering on other dimensions. In Appendix I.2, we follow Guren, McKay, Nakamura, and Steinsson (2018) and perform such a bootstrap. The estimates remain significant across almost all specifications.

[17] We describe these series in Appendix A.1.

2. Variation in the price of risk, λ_t, leads to predictable variation in mean expected MPK. Expression (3) implies that the price of risk should positively predict the level of expected MPK. To test this implication, we estimate time-series regressions of the form:

$$\mathbb{E}\left[mpk_{it+1}\right] = \psi_0 + \psi_1 \lambda_t + \zeta_{t+1}\,, \tag{6}$$

where $\mathbb{E}\left[mpk_{it+1}\right]$ denotes the average mpk in period $t+1$ and λ_t denotes three different proxies of the price of risk: the price/dividend ratio (PD) on the aggregate stock market and two measures of credit spreads – the Gilchrist and Zakrajsek (2012) (GZ) spread, a high-information and duration-adjusted measure of the mean credit spread and the excess bond (EB) premium, which measures the portion of the GZ spread not attributable to default risk.[18] These are standard proxies for risk prices that have been widely used in the literature. We estimate specification (6) using quarterly data on these measures, where the left-hand side variable is one year (four-quarter) ahead mpk.[19] Table 3 reports the results of these regressions. In line with the theory, column (1) shows that the PD ratio (likely negatively correlated with the price of risk) predicts lower future MPK, while columns (2) and (3) show that the GZ spread and the EB premium (likely positively correlated with the price of risk) predict higher future MPK. Thus, the table confirms that time-variation in risk premia forecast future levels of MPK.

Table 3: Predictability of Mean MPK

	(1)	(2)	(3)
PD Ratio	-0.341***		
	(-3.24)		
GZ Spread		4.457***	
		(3.44)	
EB Premium			7.041***
			(3.20)
Observations	166	166	166
R^2	0.120	0.122	0.100

Notes: This table reports time-series regressions of four-quarter ahead average mpk on measures of the price of risk. t-statistics are in parentheses, which are computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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[18]We extract the cyclical component of the PD ratio and mean mpk using a one-sided Hodrick-Prescott filter. The credit spread measures do not exhibit significant longer-term trends.

[19]To control for the changing composition of firms, for each quarter, we include only firms that were present in the previous quarter and calculate changes in the mean mpk for these firms. We then use those changes to construct a composition-adjusted series for mean mpk which is unaffected by new additions or deletions from the dataset. We further detail this procedure in Appendix A.1.

3. MPK dispersion is related to beta dispersion. Expression (4) implies that across groups of firms or segments of the economy, dispersion in expected MPK should be positively related to dispersion in risk exposures. We investigate this prediction using variation in the dispersion of firm-level betas and expected stock market returns across industries. Specifically, for each industry in each year, we compute the standard deviation of MPK, $\sigma\left(mpk\right)$, expected stock returns, $\sigma\left(\mathbb{E}\left[r\right]\right)$, and beta, $\sigma\left(\beta\right)$. We then estimate regressions of industry-level MPK dispersion on the dispersion in expected returns and betas, i.e.,

$$\sigma\left(mpk_{jt+1}\right) = \psi_0 + \psi_1\sigma\left(x_{jt}\right) + \zeta_{jt+1} \quad x_{jt} = \mathbb{E}\left[r_{jt}\right], \beta_{jt} \ ,$$

where j denotes industry. Again, to avoid potential simultaneity biases from the realization of shocks, we lag the independent variables (dispersion in expected returns and betas).

Table 4 reports the results of these regressions and demonstrates that indeed, industries with higher dispersion in expected stock returns and beta exhibit greater dispersion in MPK. Column (1) reveals this fact using expected returns calculated from the Fama-French model.[20] Variation in expected return dispersion predicted by the Fama-French model explains over 20% of the variation in MPK dispersion across industry-years. Column (2) regresses MPK dispersion on dispersion in each of the three individual factors – variation in the beta on each factor is significantly related to MPK dispersion. Next, we repeat the exercise using dispersion in MPK betas (described above) as the right-hand side variables. The results in column (3) show that industries with greater dispersion in MPK betas (on each of the Fama-French factors) exhibit greater dispersion in MPK. Columns (4)-(6) add year fixed-effects and a number of controls capturing additional measures of firm heterogeneity within industries – the standard deviations of profitability, size, book-to-market, and market leverage. Across these specifications, measures of within-industry heterogeneity in expected returns and aggregate risk exposures remain positive and significant predictors of within-industry dispersion in MPK.[21]

4. MPK dispersion is positively correlated with the price of risk. Expression (4) implies that the price of risk is positively related to MPK dispersion. We investigate this prediction in two ways. First, we show that the indicators of the price of risk considered before (PD ratio, GZ spread, and EB premium) predict time-series variation in MPK dispersion. Second, we show that the

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[20]Expected returns are computed using a standard two-stage approach – first, we estimate the betas from time-series regressions as described under prediction 1. We then measure expected returns as the predicted values from cross-sectional Fama-Macbeth regressions of returns on these betas. We provide further details in Appendix A.1.

[21]The results are robust to using different asset pricing models to compute betas and expected returns, such as the CAPM and Hou et al. (2015) investment-CAPM models. The relationship is robust to a variety of different controls and industry definitions as well. Finally, the results are qualitatively similar when we use the inter-quartile range instead of the standard deviation as our measure of within-industry dispersion.

Table 4: Industry-Level Dispersion in MPK, Expected Stock Returns and Beta

	(1)	(2)	(3)	(4)	(5)	(6)
$\sigma(\mathbb{E}[r])$	2.71***			1.20***		
	(30.11)			(9.82)		
$\sigma(\beta_{MKT})$		0.11***			0.08***	
		(6.48)			(3.31)	
$\sigma(\beta_{HML})$		0.14***			0.10***	
		(11.18)			(5.61)	
$\sigma(\beta_{SMB})$		0.14***			0.07***	
		(13.72)			(5.77)	
$\sigma(\beta_{CAPM,MPK})$			0.01***			0.09***
			(8.58)			(4.08)
$\sigma(\beta_{HML,MPK})$			0.06***			0.06***
			(7.96)			(4.80)
$\sigma(\beta_{SMB,MPK})$			0.06***			0.06***
			(10.38)			(5.70)
Observations	3203	3210	2398	3188	3194	2380
R^2	0.221	0.265	0.200	0.261	0.285	0.348
Industries	157	161	142	153	156	138
Year F.E.	No	No	No	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes

Notes: This table reports a panel regression of the dispersion in *mpk* within industries on lagged measures of dispersion in risk exposure within those industries. An observation is an industry-year. $\mathbb{E}[r]$ is the expected return computed from the Fama-French model. β denotes the stock return beta on the Fama-French factors and β_{MPK} the *mpk* beta on the same factors. *t*-statistics are in parentheses. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

expected return on the high-minus-low MPK portfolio is also predicted by these measures.

To perform these tests, we estimate regressions of the form

$$y_{t+1} = \psi_0 + \psi_1 \lambda_t + \zeta_{t+1}, \quad y_{t+1} = \sigma(mpk_{t+1}), r_{HML,t+1},$$

where λ_t denotes the various proxies for the price of risk. Columns (1)-(3) of table 5 report regressions of the within-industry standard deviation of MPK, $\sigma(mpk_{t+1})$, on the lagged values of these measures. Each predicts MPK dispersion, and in the direction the theory suggests: the GZ Spread and excess bond premium predict greater MPK dispersion, while a higher PD ratio predicts lower dispersion.[22] Because our measures of the price of risk are countercyclical, the results imply that variation in risk premia induce a countercyclical component in MPK

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[22]We again extract the cyclical component of the PD ratio and *mpk* dispersion using a one-sided Hodrick-Prescott filter. The results are qualitatively similar when we use a measure of unconditional (not industry-adjusted) MPK dispersion as the dependent variable.

dispersion, in line with (and potentially in part accounting for) the well known evidence of countercyclicality documented in Eisfeldt and Rampini (2006).[23]

Table 5: Predictability of MPK Dispersion and MPK-HML Portfolio Return

	MPK Dispersion			MPK-HML Portfolio Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
PD Ratio	-0.112***			-0.013*		
	(-3.52)			(-1.84)		
GZ Spread		1.226***			0.269**	
		(3.23)			(2.27)	
EB Premium			3.415***			0.426**
			(4.44)			(2.32)
Observations	166	166	166	166	166	166
R^2	0.103	0.072	0.185	0.031	0.082	0.068

Notes: This table reports time-series regressions of four-quarter ahead *mpk* dispersion and MPK-HML portfolio returns on measures of the price of risk. *t*-statistics are in parentheses, computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, columns (4)-(6) of Table 5 report regressions using the cumulative twelve month return on the MPK-HML portfolio, $r_{HML,t+1}$ as the dependent variable. The GZ spread and excess bond premium predict higher future returns on the MPK-HML portfolio, while the PD ratio predicts lower future returns, implying that a high price of risk predicts a greater return spread between high and low MPK firms. In sum, our findings confirm that indeed, investors require greater compensation (in the form of a higher rate of return) to invest in high MPK firms at times when risk premia are high, leading to a predictable and countercyclical increase in dispersion and widening of the spread between low and high MPK firms.[24]

4 Quantitative Model

In the next two sections, we use a more detailed version of the investment model laid out above to quantitatively investigate the contribution of heterogeneous risk premia to observed MPK dispersion. The model is kept deliberately simple in order to isolate the role of our basic mechanism, namely dispersion in exposure to systematic risk. The theory consists of two main building blocks: (i) a stochastic discount factor, which we directly parameterize to be consistent with salient patterns in financial markets, i.e., high and countercyclical prices of risk and (ii) a cross-section of heterogeneous firms, which make optimal investment decisions in

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[23]We report the correlations of these measures with de-trended GDP and TFP in Table 8 in Appendix A.2.
[24]De-trended GDP also predicts countercyclical dispersion and return spreads.

the presence of firm-level and aggregate risk, given the stochastic discount factor. Specifying the stochastic discount factor exogenously allows us to sidetrack challenges with generating empirically relevant risk prices in general equilibrium, and focus on gauging the quantitative strength of our mechanism. To hone in on the effects of risk premia, we begin with a simplified version in which we abstract from additional adjustment frictions. In this case, our framework yields exact closed form solutions for firm investment decisions. In Section 4.3, we extend the model to include capital adjustment costs. Our theoretical results there reveal an important amplification effect of these costs on the impact of risk premia.[25]

4.1 The Environment

Heterogeneity in risk exposures. The setup is a fleshed-out version of that in Section 2. We consider a discrete time, infinite-horizon economy. A continuum of firms of fixed measure one, indexed by i, produce a homogeneous good using capital and labor according to:

$$Y_{it} = X_t^{\hat{\beta}_i} \hat{Z}_{it} K_{it}^{\theta_1} N_{it}^{\theta_2}, \quad \theta_1 + \theta_2 < 1 . \tag{7}$$

Firm productivity (in logs) is equal to $\hat{\beta}_i x_t + \hat{z}_{it}$, where x_t denotes an aggregate component that is common across firms and $\hat{\beta}_i$ captures the exposure of the productivity of firm i to aggregate conditions. We assume that $\hat{\beta}_i$ is distributed as $\hat{\beta}_i \sim \mathcal{N}\left(\bar{\hat{\beta}}, \sigma_{\hat{\beta}}^2\right)$ across firms. Heterogeneity in this exposure is a key ingredient of our framework – cross-sectional variation in $\hat{\beta}_i$ will lead directly to dispersion in expected MPK. The term $\hat{z}_{it}$ denotes a firm-specific, idiosyncratic component of productivity.[26]

The two productivity components follow AR(1) processes (in logs):

$$
\begin{aligned}
x_{t+1} &= \rho_x x_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}\left(0, \sigma_\varepsilon^2\right) \\
\hat{z}_{it+1} &= \rho_z \hat{z}_{it} + \hat{\varepsilon}_{it+1}, \quad \hat{\varepsilon}_{it+1} \sim \mathcal{N}\left(0, \sigma_{\hat{\varepsilon}}^2\right) .
\end{aligned}
\tag{8}
$$

Thus, there are two sources of uncertainty at the firm level – aggregate uncertainty, with conditional variance σ_ε^2, and idiosyncratic uncertainty, with variance $\hat{\sigma}_{\hat{\varepsilon}}^2$.

Stochastic discount factor. In line with the large literature on cross-sectional asset pricing in production economies, we parameterize directly the pricing kernel without explicitly modeling

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[25]We also consider the effects of other investment frictions, e.g., "wedges," or distortions, in Section 5.3.

[26]More broadly, expression (7) should be thought of as a revenue-generating function and the "productivity" components as also capturing demand factors, see, e.g,. Section 6.

the consumer's problem. In particular, we specify the SDF as

$$\log M_{t+1} \equiv m_{t+1} = \log \rho - \gamma_t \varepsilon_{t+1} - \frac{1}{2}\gamma_t^2 \sigma_\varepsilon^2 \tag{9}$$
$$\gamma_t = \gamma_0 + \gamma_1 x_t \, ,$$

where ρ, $\gamma_0 > 0$ and $\gamma_1 \leq 0$ are constant parameters.[27] The SDF is determined by shocks to aggregate productivity. The conditional volatility of the SDF, $\sigma_m = \gamma_t \sigma_\varepsilon$, varies through time as determined by γ_t. This formulation allows us to capture in a simple manner a high, time-varying and countercyclical price of risk as observed in the data (since $\gamma_1 < 0$, γ_t is higher following economic contractions, i.e., when x_t is negative). Additionally, directly parameterizing γ_0 and γ_1 enables the model to be quantitatively consistent with key moments of asset returns, which are important for our analysis. The risk free rate is constant and equal to $-\log \rho$. Thus, γ_0 and γ_1 only affect the properties of equity returns., easing the interpretation of these parameters. The maximum attainable Sharpe ratio is equal to the conditional standard deviation of the SDF, i.e., $SR_t = \gamma_t \sigma_\varepsilon$, and the price of risk is equal to the square of the Sharpe ratio, $\gamma_t^2 \sigma_\varepsilon^2$.

For simplicity, the setup thus far features (i) a single source of aggregate risk and (ii) a tight link between financial market conditions (i.e., γ_t) and macroeconomic conditions (i.e., x_t). In Appendix E we extend this framework to (i) include multiple risk factors and (ii) decouple movements in financial and macroeconomic conditions by including pure financial shocks that affect the price of risk but otherwise do not impact firm profits/productivity. Similar insights from the simpler model go through under those extensions.

Input choices. Firms hire labor period-by-period at a competitive wage, W_t. To keep the labor market simple, we assume that the equilibrium wage is given by

$$W_t = X_t^\omega \, ,$$

i.e., the wage is a constant elasticity and increasing function of aggregate productivity, where $\omega \in [0, 1]$ determines the sensitivity of wages to aggregate conditions.[28] Maximizing over the static labor decision gives operating profits – revenues less labor costs – as

$$\Pi_{it} = G X_t^{\beta_i} Z_{it} K_{it}^\theta \, , \tag{10}$$

where $G \equiv (1 - \theta_2) \theta_2^{\frac{\theta_2}{1-\theta_2}}$, $\beta_i \equiv \frac{1}{1-\theta_2}\left(\hat{\beta}_i - \omega\theta_2\right)$, $Z_{it} \equiv \hat{Z}_{it}^{\frac{1}{1-\theta_2}}$ and $\theta \equiv \frac{\theta_1}{1-\theta_2}$. The exposure of firm profits to aggregate conditions is captured by β_i, which is a simple transformation of the

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[27]This specification builds closely on those in, for example, Zhang (2005) and Jones and Tuzel (2013).

[28]This setup follows, for example, Belo et al. (2014) and İmrohoroğlu and Tüzel (2014).

underlying exposure of firm productivity to the aggregate component, $\hat{\beta}_i$, and the sensitivity of wages, ω.[29] The idiosyncratic component of productivity is similarly scaled, by $\frac{1}{1-\theta_2}$. The curvature of the profit function is equal to θ, which depends on the relative elasticities of capital and labor in production. These scalings reflect the leverage effects of labor liabilities on profits. From here on, we will primarily work with z_{it}, which has the same persistence as $\hat{z}_{it}$, i.e., ρ_z, and innovations $\varepsilon_{it+1} = \frac{1}{1-\theta_2}\hat{\varepsilon}_{t+1}$ with variance $\sigma_{\tilde{\varepsilon}}^2 = \left(\frac{1}{1-\theta_2}\right)^2 \sigma_{\hat{\varepsilon}}^2$. We will also use the fact that $\sigma_{\beta}^2 = \left(\frac{1}{1-\theta_2}\right)^2 \sigma_{\hat{\beta}}^2$. Notice that the profit function takes precisely the form assumed in Section 2. Thus, the firm's dynamic investment problem takes the form in expression (1).

Optimal investment.   The simplicity of this setting leads to exact analytical expressions for the firm's investment decision. Specifically, we show in Appendix C.1 that the firm's optimal investment policy is given by:

$$ k_{it+1} = \frac{1}{1-\theta} \left(\tilde{\alpha} + \beta_i \rho_x x_t + \rho_z z_{it} - \beta_i \gamma_t \sigma_\varepsilon^2 \right) \ , \tag{11} $$

where $\tilde{\alpha} \equiv \log \theta + \log G - \alpha$, $\alpha \equiv r_f + \log(1 - (1-\delta)\rho)$.[30]   The firm's choice of capital is increasing in x_t and z_{it} due to their direct effect on expected future productivity (i.e., $\beta_i \rho_x x_t + \rho_z z_{it} = \mathbb{E}_t[\beta_i x_{t+1} + z_{it+1}]$), but, *ceteris paribus*, firms with higher betas choose a lower level of capital. The magnitude of this effect is larger when γ_t is large, i.e., in economic downturns. Clearly, with risk neutrality, i.e., $\gamma_0 = \gamma_1 = 0$, the last term is zero and investment is purely determined by expected productivity.

For a slightly different intuition, we substitute for γ_t and write the expression as

$$ k_{it+1} = \frac{1}{1-\theta} \left(\tilde{\alpha} + \beta_i \left(\rho_x - \gamma_1 \sigma_\varepsilon^2 \right) x_t + \rho_z z_{it} - \beta_i \gamma_0 \sigma_\varepsilon^2 \right) \ . \tag{12} $$

The risk premium affects the capital choice through both the time-varying and constant components of the price of risk: first, a more negative γ_1 increases the responsiveness of firms to aggregate conditions. Intuitively, a high (low) realization of x_t has two effects – first, since x_t is persistent, it signals that productivity is likely to be high (low) in the future, increasing (decreasing) investment (this force is captured by the ρ_x term). Moreover, a high (low) realization of x_t implies a low (high) price of risk, which further increases (decreases) investment. Second, the constant component of the risk premium, γ_0, adds a firm-specific constant – i.e., a

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[29]The adjustment term for labor supply, $\omega\theta_2$, has a small effect on the mean of the β distribution, but otherwise does not affect our analysis.

[30]More precisely, there are also terms that reflect the variance of shocks. Because these terms are negligible and play no role in our analysis (they are independent of the risk premium effects we measure), we suppress them here. The full expressions are given in Appendix C.1.

fixed-effect – which leads to permanent dispersion in firm-level capital.

MPK dispersion. By definition, the realized mpk is given by $mpk_{it+1} = \log\theta + \pi_{it+1} - k_{it+1}$. Substituting for k_{it+1},

$$mpk_{it+1} = \alpha + \varepsilon_{it+1} + \beta_i\varepsilon_{t+1} + \beta_i\gamma_t\sigma_\varepsilon^2 \ , \tag{13}$$

and taking conditional expectations,

$$Empk_{it+1} \equiv \mathbb{E}_t\left[mpk_{it+1}\right] = \alpha + \beta_i\gamma_t\sigma_\varepsilon^2 \ , \tag{14}$$

where α is as defined in equation (11) and reflects the risk-free user cost of capital. Expression (13) shows that dispersion in the realized mpk can stem from uncertainty over the realization of shocks, as well as the risk premium term, which is persistent at the firm level and depends on (i) the firm's exposure to the aggregate shock, β_i (and is increasing in β_i), and (ii) the time t price of risk, which is reflected in the term $\gamma_t\sigma_\varepsilon^2$. Intuitively, firm-level mpk deviations are composed of both a transitory component due to uncertainty and a persistent component due to the risk premium. The transitory components are i.i.d. over time and lead to purely temporary deviations in mpk (even though the underlying productivity processes are autocorrelated); the risk premium, on the other hand, leads to persistent deviations – firms that are more exposed to aggregate shocks, and so are riskier, will have persistently high mpk.

Expression (14) hones in on this second force and shows the persistent effects of risk premia on the conditional expectation of time $t+1$ mpk, denoted $Empk$. Indeed, in this simple case, the ranking of firms' mpk will be constant in expectation as determined by the risk premium – high beta firms will have permanently high $Empk$ and low beta firms the opposite. Importantly, the *value* of $Empk$ will fluctuate with γ_t, but the ordering across firms will be preserved. This is the sense that we call this component persistent/permanent. Expression (13) shows that this ordering will not be preserved in realized mpk – due to the realization of shocks, the ranking of firms' mpk will fluctuate, but the firm-specific risk premium adds a persistent component.[31] Because the uncertainty portion of the realized mpk is always additively separable and is independent of our mechanism, from here on we primarily work with $Empk$.

Expression (15) presents the cross-sectional variance of $Empk$:

$$\sigma_{Empk_t}^2 \equiv \sigma_{\mathbb{E}_t[mpk_{it+1}]}^2 = \sigma_\beta^2 \left(\gamma_t\sigma_\varepsilon^2\right)^2 \ . \tag{15}$$

Cross-sectional variation in $Empk$ depends on the dispersion in beta and the price of risk. Dispersion will be greater when risk prices, reflected by $\gamma_t\sigma_\varepsilon^2$, are high and so will be countercyclical.

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[31]With additional adjustment frictions, there will be other factors confounding the relationship between beta and the realized and expected mpk.

The average long-run level of $Empk$ dispersion is given by

$$E\sigma^2_{Empk} \equiv \mathbb{E}\left[\sigma^2_{Empk_t}\right] = \sigma^2_\beta \left(\gamma_0^2 + \gamma_1^2 \sigma_x^2\right)\left(\sigma_\varepsilon^2\right)^2 \quad \text{where} \quad \sigma_x^2 = \frac{\sigma_\varepsilon^2}{1 - \rho_x^2}\,. \tag{16}$$

An examination of expressions (14) and (15) confirms that the richer model here is consistent with the four key implications from Section 2, namely – (1) exposure to risk factors is a determinant of $Empk$; (2) variation in the price of risk leads to predictable variation in mean $Empk$; (3) mpk dispersion is related to beta dispersion; and (4) mpk dispersion is increasing in the price of risk, and so naturally contains a countercyclical element.

Aggregate outcomes. What are the implications of this dispersion in $Empk$ for the aggregate economy? Appendix C.3 shows that aggregate output can be expressed as

$$\log Y_{t+1} \equiv y_{t+1} = a_{t+1} + \theta_1 k_{t+1} + \theta_2 n_{t+1}\,,$$

where k_{t+1} denotes the aggregate capital stock, n_{t+1} aggregate labor and a_{t+1} the level of aggregate TFP, given by

$$a_{t+1} = a^*_{t+1} - \frac{1}{2}\frac{\theta_1(1-\theta_2)}{1-\theta_1-\theta_2}\sigma^2_{mpk,t+1}\,, \tag{17}$$

where $\sigma^2_{mpk,t+1}$ is realized mpk dispersion in period $t+1$. The term a^*_{t+1} is the first-best level of TFP in the absence of any frictions (i.e., where marginal products are equalized). Thus, aggregate TFP monotonically decreases in the extent of capital "misallocation," captured by σ^2_{mpk}. The effect of misallocation on aggregate TFP depends on the overall curvature in the production function, $\theta_1 + \theta_2$ and the relative shares of capital and labor. The higher is $\theta_1 + \theta_2$, that is, the closer to constant returns to scale, the more severe the losses from mis-allocated resources. Similarly, fixing the degree of overall returns to scale, for a larger capital share, θ_1, a given degree of misallocation has larger effects on aggregate outcomes.

Using equation (15), the conditional expectation of one-period ahead TFP is given by

$$\mathbb{E}_t\left[a_{t+1}\right] = \mathbb{E}_t\left[a^*_{t+1}\right] - \frac{1}{2}\frac{\theta_1(1-\theta_2)}{1-\theta_1+\theta_2}\sigma^2_\beta\left(\gamma_t\sigma_\varepsilon^2\right)^2\,. \tag{18}$$

The expression shows that risk premium effects unambiguously reduce aggregate TFP and disproportionately more so in business cycle downturns, since γ_t is countercyclical. Taking unconditional expectations gives the effects on the average long-run level of TFP in the economy:

$$\bar{a} \equiv \mathbb{E}\left[\mathbb{E}_t\left[a_{t+1}\right]\right] = a^* - \frac{1}{2}\frac{\theta_1(1-\theta_2)}{1-\theta_1+\theta_2}\sigma^2_\beta\left(\gamma_0^2 + \gamma_1^2\sigma_x^2\right)\left(\sigma_\varepsilon^2\right)^2\,. \tag{19}$$

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The expression directly links the extent of cross-sectional dispersion in required rates of return (which are in turn determined by the prices of risk and volatility of aggregate shocks) to the long-run level of aggregate productivity and gives a natural way to quantify the implications of these effects. Further, and perhaps more importantly, it uncovers a new connection between aggregate volatility and long-run economic outcomes, i.e., a "productivity cost" of business cycles – *ceteris paribus*, the higher is aggregate volatility (σ_ε^2 and σ_x^2 in the expression), the more depressed will be the average long-run level of TFP (relative to an environment with no aggregate shocks and/or risk premia).

In Appendix E, we show that our model can be extended to include multiple risk factors and to allow γ_t to depend on additional factors beyond the state of technology and so expressions (18) and (19) provide a more general connection between financial conditions (that may be less than perfectly correlated with the real economy) and aggregate productivity. Thus, more broadly, these expressions provide one way to link the rich findings of the literature on cross-sectional asset pricing to real allocations and measures of aggregate performance.

4.2   The Cross-Section of Expected Stock Returns and MPK

In this section, we derive a sharp link between a firm's beta – and so its expected mpk – and its expected stock market return. This connection suggests an empirical strategy to measure the dispersion in beta and so quantify the mpk dispersion that arises from risk considerations using stock market data. Our key finding is that, to a first-order approximation, the firm's expected stock return is a linear (and increasing) function of its beta.[32] Indeed, in the simple model outlined thus far, expected mpk is proportional to expected stock returns. This link, first, justifies our use of data on expected stock returns and stock market betas as a proxy for expected mpk in Section 3 and second, shows that the dispersion in expected stock returns puts tight empirical discipline on the dispersion in betas and so expected mpk arising from risk channels – indeed, under some circumstances, they are proportional to one another. We use this connection to provide transparent intuition for our numerical approach in Section 5.

We obtain an analytic approximation for expected stock market returns by log-linearizing around the non-stochastic steady state where $X_t = Z_t = 1$. To a first-order, the (log of the) expected excess stock return is equal to (derivations in Appendix C.4)

$$Er_{it+1}^e \equiv \log \mathbb{E}_t \left[R_{it+1}^e \right] = \psi \beta_i \gamma_t \sigma_\varepsilon^2 \,, \tag{20}$$

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[32]It is well known that a first-order approximation may not be sufficient to capture risk premia. In our quantitative work in Section 5, we work with numerical higher order approximations.

where

$$\psi = \frac{\frac{1}{\rho} + \delta - 1}{\frac{1}{\rho} + \delta(1-\theta) - 1} \frac{1-\rho}{1 - \rho\rho_x + \rho\gamma_1\sigma_\varepsilon^2} .$$

The expected excess return depends on the firm's beta (indeed, is linear and increasing in beta) and is increasing in the price of risk. Because the price of risk is countercyclical, risk premia increase during downturns for all firms and fall during expansions.[33] The time t cross-sectional dispersion in expected excess returns is given by

$$\sigma_{Er_t^e}^2 \equiv \sigma_{\log \mathbb{E}_t[R_{it+1}^e]}^2 = \psi^2 \sigma_\beta^2 \left(\gamma_t \sigma_\varepsilon^2\right)^2 . \tag{21}$$

Similar to our findings for expected mpk, the expression reveals a tight link between beta dispersion and expected stock return dispersion. Indeed, if firms had identical betas, dispersion in expected returns would be zero. Moreover, as with expected mpk dispersion, expected stock return dispersion is increasing in the price of risk and so is countercyclical.

Comparing equations (14) and (20) shows that expected excess returns, Er_{it+1}^e, are proportional to expected mpk, $Empk_{it+1}$ and equations (15) and (21) show that $\sigma_{Er_t^e}^2$ is proportional to $\sigma_{Empk_t}^2$. Thus, the expressions reveal a tight connection between cross-sectional variation in expected stock returns and expected mpk – both are dependent on the variation in betas. Although the exact proportionality will not hold in the full non-linear solution, we will use this intuition to quantify the role of risk considerations in generating dispersion in expected mpk.

Specifically, these results suggest an empirical strategy to estimate the three key structural parameters – γ_0, γ_1 and σ_β^2 – using readily available stock market data. First, it is straightforward to verify that the market index – i.e., a perfectly diversified portfolio with no idiosyncratic risk – achieves the maximal Sharpe ratio:[34]

$$SR_{mt} = \gamma_t \sigma_\varepsilon, \qquad ESR_m \equiv \mathbb{E}[SR_{mt}] = \gamma_0 \sigma_\varepsilon . \tag{22}$$

The expression links the market Sharpe ratio to γ_0. Indeed, in this linearized environment, the mapping is one-to-one (given σ_ε^2). Next, deriving equation (20) for the market index gives

$$Er_{mt+1} = \psi\bar{\beta}\gamma_t\sigma_\varepsilon^2, \qquad Er_m \equiv \mathbb{E}[Er_{mt+1}] = \psi\bar{\beta}\gamma_0\sigma_\varepsilon^2 . \tag{23}$$

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[33]Strictly speaking, these results hold in the approximation so long as $1 - \rho\rho_x + \rho\gamma_1\sigma_\varepsilon^2 > 0$. This condition does not play a role in the numerical solution.

[34]The Sharpe ratio for an individual firm is $SR_{it} = \frac{\beta_i\gamma_t\sigma_\varepsilon^2}{\sqrt{\left(\frac{1 - \rho\rho_x + \rho\gamma_1\sigma_\varepsilon^2}{1 - \rho\rho_z}\right)^2 \sigma_\varepsilon^2 + \beta_i^2\sigma_\varepsilon^2}}$, which shows that, due to the

presence of idiosyncratic risk, individual firms do not attain the maximum Sharpe ratio. However, in this linear environment, the diversified index faces no risk from σ_ε^2, so that the expression collapses to (22). Although in the full numerical solution the market may not exactly attain this value due to the nonlinear effects of idiosyncratic shocks, the expression highlights that the market Sharpe ratio is informative about γ_0.

For a given value of γ_0, the equity premium is increasing as γ_1 becomes more negative through its effects on ψ ($\bar{\beta}$ denotes the mean beta across firms). Lastly, equation (21) connects dispersion in beta, σ_β^2, to dispersion in expected returns. Together, equations (21), (22) and (23) tightly link three observable moments of asset market data to the three parameters, γ_0, γ_1 and σ_β^2.

4.3 Adjustment Costs

In this section, we extend our framework to include capital adjustment costs. Although the main insights from the previous sections go through, we illustrate an important interaction between these costs and the effects of risk premia, namely, adjustment costs amplify the impact of these systematic risk exposures on mpk dispersion.

We assume that capital investment is subject to quadratic adjustment costs, given by

$$\Phi\left(I_{it}, K_{it}\right) = \frac{\xi}{2}\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} .$$

With these costs, exact analytic solutions are no longer available. Appendix C.2 sets up the firm's problem and derives the log-linearized version of the firm's optimal investment policy:

$$k_{it+1} = \phi_{00} + \phi_1 \beta_i x_t + \phi_2 z_{it} + \phi_3 k_{it} - \phi_{01}\beta_i , \tag{24}$$

where

$$0 = \left((\theta - 1) - \hat{\xi}(1 + \rho)\right)\phi_3 + \rho\hat{\xi}\phi_3^2 + \hat{\xi}$$

$$\phi_1 = \frac{\left(\rho_x - \gamma_1 \sigma_\varepsilon^2\right)\phi_3}{\hat{\xi}\left(1 - \rho\rho_x\phi_3 + \rho\gamma_1\sigma_\varepsilon^2\phi_3\right)}, \qquad \phi_2 = \frac{\rho_z\phi_3}{\hat{\xi}\left(1 - \rho\rho_z\phi_3\right)}$$

$$\phi_{01} = \frac{\phi_3}{\hat{\xi}\left(1 - \rho\phi_3\right)}\frac{\gamma_0\sigma_\varepsilon^2}{1 - \rho\rho_x\phi_3 + \rho\gamma_1\sigma_\varepsilon^2\phi_3} .$$

We characterize the constant, ϕ_{00}, in the Appendix.[35] The term $\hat{\xi}$ is a composite parameter that captures the severity of adjustment costs, defined by $\hat{\xi} \equiv \frac{\xi}{1-\rho(1-\delta)}$.

Now, the past level of capital affects the new chosen level. The coefficient ϕ_3 captures the strength of this relationship. It lies between zero and one and is increasing in the adjustment cost, $\hat{\xi}$. It is independent of the risk premium. The other coefficients each have a counterpart in equation (12), but are modified to reflect the influence of adjustment costs. The coefficients ϕ_1 and ϕ_2 are both decreasing in these costs – intuitively, adjustment costs reduce the firm's responsiveness to transitory shocks. Importantly, ϕ_{01} is increasing in these costs, showing that

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[35]As above, we ignore terms reflecting variance adjustments that are close to zero.

they increase the importance of the firm's beta in determining its choice of capital.[36] The expression for ϕ_{01} also reveals an interaction between adjustment costs and time-varying risk – the denominator contains the product of ϕ_3 and γ_1, which implies that a more negative γ_1 leads to higher values of ϕ_{01} as long as adjustment costs are non-zero. By increasing the value of ϕ_{01}, this interaction effect strengthens the impact of beta dispersion on $Empk$ dispersion.

Risk premium effects and adjustment costs can both lead to $Empk$ dispersion (realized mpk dispersion also depends on uncertainty, as above). Closed-form solutions are not available for period-by-period dispersion. However, to gain intuition, we are able to characterize the mean of firm-level expected mpk (which is also the mean of realized mpk) and its dispersion:

$$\mathbb{E}\left[Empk_{it+1}\right] = -\frac{1-\theta}{1-\phi_3}\left(\phi_{00} - \phi_{01}\beta_i\right) \quad \Rightarrow \quad \sigma^2_{\mathbb{E}[Empk_{it+1}]} = \left(\frac{1-\theta}{1-\phi_3}\right)^2 \phi_{01}^2 \sigma_\beta^2 . \quad (25)$$

The extended model continues to give rise to mpk deviations that are persistent at the firm-level. Strikingly, the risk premium is a necessary ingredient for this result – ϕ_{01} is multiplicative in γ_0 so that in the absence of risk effects, there is no persistent $Empk$ dispersion, even with adjustment costs (beta dispersion is also necessary). The expression also reveals a second amplification effect of adjustment costs through the $1 - \phi_3$ term in the denominator. Recall that ϕ_3 is increasing in these costs, as is ϕ_{01}, which imply that higher adjustment costs unambiguously increase risk effects on dispersion in $Empk$. An interesting implication of this result is that, perhaps surprisingly, adjustment costs do not only affect transitory dispersion in mpk. While this is true on their own, in conjunction with a fixed component in the mpk, which we have here, these costs can serve to amplify the effects of that component.

Finally, how do adjustment costs change the relationship between expected mpk, beta and expected stock returns? Appendix C.4 shows that to a first-order, expected returns are not affected by adjustment costs and so the results from Section 4.2 continue to hold.[37] Thus, the arguments made in that section linking the key parameters of the model to moments of asset returns go through unchanged.

5 Quantitative Analysis

In this section, we use the analytical insights laid out above to numerically quantify the extent of mpk dispersion arising from risk premia effects.

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[36]Strictly speaking, this is true so long as $1 - \rho\rho_x\phi_3 + \rho\gamma_1\sigma_\varepsilon^2\phi_3 > 0$. This condition holds for any reasonable level of adjustment costs, for example, given our estimates of the other parameters, ξ must be less than approximately 2180.

[37]Although this is only exactly true under our first-order approximation, Table 7 verifies numerically that adjustment costs have relatively modest effects on moments of returns.

5.1 Parameterization

We begin by assigning values to the more standard production parameters of our model. Following Atkeson and Kehoe (2005), we set the overall returns to scale in production $\theta_1 + \theta_2$ to 0.85. We assume standard shares for capital and labor of 0.33 and 0.67, respectively, which gives $\theta_1 = 0.28$ and $\theta_2 = 0.57$. These values imply $\theta = 0.65$.[38] We assume a period length of one year and accordingly set the rate of depreciation to $\delta = 0.08$. We estimate the adjustment cost parameter, ξ, in order to match the autocorrelation of investment, denoted $\mathrm{corr}\,(\Delta k_t, \Delta k_{t-1})$, which is 0.38 in our data. Equation (31) in Appendix C.5 provides a closed-form expression for this moment, which reveals a tight connection with the severity of adjustment frictions.[39]

To estimate the parameters governing the aggregate shock process, we build a long sample of Solow residuals for the US economy using data from the Bureau of Economic Analysis on real GDP and aggregate labor and capital. The construction of this series is standard (details in Appendix A.4). With these data, we use a standard autoregression to estimate the parameters ρ_x and σ_ε^2. This procedure gives values of 0.94 and 0.0247 for the two parameters, respectively.[40] Under our assumptions, firm-level productivity (including the aggregate component) can be measured directly (up to an additive constant) as $y_{it} - \theta k_{it}$. After controlling for the level of aggregate productivity, a similar autoregression on the residual (firm-specific) component yields values for ρ_z and $\sigma_{\tilde{\varepsilon}}$ of 0.93 and 0.28, respectively.

Turning to the parameters of the SDF, we set $\rho = 0.988$ to match an average annual risk-free rate of 1.2%. Following the arguments in Section 4.2, we estimate the values of γ_0 and γ_1 to match the post-war (1947-2017) average annual excess return on the market index of 7.7% and Sharpe ratio of 0.53.[41] This strategy is equivalent to matching both the mean and volatility

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[38]This is close to the values generally used in the literature. For example, Cooper and Haltiwanger (2006) estimate a value of 0.59 for US manufacturing firms. David and Venkateswaran (2017) use a value of 0.62.

[39]The expression also reveals that for ρ_x close to ρ_z, which we find in the data, described next, the autocorrelation of within-firm investment is almost invariant to the firm's beta (indeed, the invariance is exact if $\rho_x = \rho_z$). Thus, even with dispersion in betas, we may not see large variation in this moment across firms.

[40]The autoregression does not reject the presence of a unit root at standard confidence levels. We have also worked with the annual TFP series developed by John Fernald, available at:
https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/.
These data are only available for the more recent post-war period, but also show that the series is close to a random walk (i.e., the autocorrelation of growth rates is essentially zero). A potential concern with this approach is that these series reflect not only the process on exogenous technology, but also the effects of mpk dispersion itself (since dispersion affects measured aggregate productivity). However, at our estimates, these effects are small – mpk dispersion primarily impacts the level of aggregate productivity (which does not affect our estimates of persistence or volatility) but has only a small impact on its time-series properties (we discuss these different effects in Section 5.2) – suggesting that these series are reasonable approximations to the exogenous process. Further, we have also constructed an alternative series that is free from this concern directly from the firm-level data by averaging across the firms in each year. This gives results quite similar to the baseline, $\rho_x = 0.92$ and $\sigma_\varepsilon = 0.0245$. Details are in Appendix A.4.

[41]We calculate these values using annualized monthly excess returns obtained from Kenneth French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

of market excess returns (the standard deviation is 14.6%). To be comparable to the data, stock returns in the model need to be adjusted for financial leverage. To do so, we scale the mean and standard deviation of the model-implied returns by a factor of $1 + \frac{D}{E}$ where $\frac{D}{E}$ is the debt-to-equity ratio. We follow, e.g., Barro (2006) and assume an average debt-to-equity ratio of 0.5. Because both the numerator and denominator are scaled by the same constant, the Sharpe ratio is unaffected. For ease of interpretation, in what follows, we report the properties of levered returns. To compute the model-implied market return, we must also take a stand on the mean beta across firms. Assuming that the mean of $\hat{\beta}_i$ (the underlying productivity beta) is one, and using the value of ω (the sensitivity of wages to aggregate shocks) suggested by İmrohoroğlu and Tüzel (2014) of 0.20, we can compute the mean beta to be 1.99.[42] This is simply the mean productivity beta adjusted for the leverage effects of labor liabilities. This procedure yields values of $\gamma_0 = 32$ and $\gamma_1 = -140$.

Finally, again following the insights in Section 4.2, we estimate the dispersion in betas to match the cross-sectional dispersion in expected stock returns. Because expected returns are not directly observable, we must choose an asset pricing model with which to estimate them. To be consistent with the broad literature, we use the expected returns predicted from the Fama-French model as computed in Section 3. We de-lever firm-level expected returns following the approach in Bharath and Shumway (2008) and Gilchrist and Zakrajsek (2012) (details in Appendix A.3). This procedure yields an estimated average within-industry standard deviation of un-levered expected returns of 0.127 (we report details and plot the full histogram of the expected return distribution in Appendix A.3: for example, the mean is about 9%, and the interquartile range is just under 12%; the standard deviation of raw expected returns, i.e., not de-levered or controlling for industry, is about 0.156).[43] Feeding this value into our quantitative model yields an estimate for σ_β of 12, and adjusting for the scaling $1 - \theta_2$ gives the dispersion in underlying productivity betas, $\sigma_{\hat{\beta}}$, equal to 4.80.[44]

We parameterize the model using simulated method of moments (details in Appendix D). Table 6 summarizes our empirical approach/results.

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[42]İmrohoroğlu and Tüzel (2014) estimate this value to match the cyclicality of wages.

[43]Our estimates are consistent with those in Lewellen (2015), who reports moments of the expected return distribution from a number of predictive models. For example, using monthly data, he finds an annualized cross-sectional standard deviation of up to 17.5% (Model 3, Panel A, Table 5 of that paper).

[44]Although this a significant amount of dispersion, it composes only a modest fraction of overall dispersion in firm-level productivity. To see this, note that the cross-sectional variance of productivity at time t is $\left(\frac{\sigma_{\hat{\beta}}}{1-\theta_2}\right)^2 x_t^2 + \sigma_z^2$, where $\sigma_z^2 = \frac{\sigma_\varepsilon^2}{1-\rho_z^2}$. Plugging in our estimates and assuming, for example, that the economy is 2% above or below trend, gives the first term to be about 8% of the total. It remains relatively modest for reasonable deviations from trend. Thus, despite firms' diverse sensitivities to business cycle shocks, our estimates still point to firm-level idiosyncratic conditions as the dominate factor driving cross-sectional heterogeneity.

Table 6: Parameterization - Summary

Parameter	Description	Value
Production		
θ_1	Capital share	0.28
θ_2	Labor share	0.57
δ	Depreciation rate	0.08
ξ	Adjustment cost	0.04
$\sigma_{\hat{\beta}}$	Std. dev. of risk exposures	4.80
Stochastic Processes		
ρ_x	Persistence of agg. shock	0.94
σ_ε	Std. dev. of agg. shock	0.0247
ρ_z	Persistence of idiosyncratic shock	0.93
$\sigma_{\tilde{\varepsilon}}$	Std. dev. of idiosyncratic shock	0.28
ω	Wage elasticity	0.20
Stochastic Discount Factor		
ρ	Time discount rate	0.988
γ_0	SDF – constant component	32
γ_1	SDF – time-varying component	-140

5.2 Risk-Based Dispersion in MPK

Table 7 presents our main quantitative results. We report four variants of our framework. The first column ("Baseline") corresponds to our full model with time-varying risk and adjustment costs. In the second column ("Only Risk"), we report the effects of risk premia without adjustment costs (i.e., ignoring the interaction effects demonstrated above). The third column ("Constant Risk") examines a version with adjustment costs but a constant price of risk (i.e., $\gamma_1 = 0$). The last column ("Only Constant Risk") has a constant price of risk and no adjustment costs. Our goal in showing these different permutations is to understand the role that each element of our model plays in leading to various patterns in mpk dispersion.

Long-run effects. The first row of the table shows the average level of mpk dispersion that stems from heterogeneous risk exposures.[45] The second row shows the percentage of total observed misallocation that this value accounts for. In our sample, overall σ^2_{mpk} is 0.45. This is the denominator in that row. Next, we calculate the dispersion stemming from only the permanent component of firm-level MPK deviations (given by equation (25)), which we report in the third row of the table. To compute this value in the data, for each firm, we regress the time-series of its mpk on a firm-level fixed effect. The fixed-effect is the permanent component

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[45]With adjustment costs, we do not have analytic expressions for period-by-period $Empk$ dispersion. We compute these values using simulation and then average over them. Without adjustment costs, we can use expression (16) directly.

Table 7: Risk Premia and Misallocation

	Baseline (1)	Only Risk (2)	Constant Risk (3)	Only Constant Risk (4)
MPK Implications				
$E\sigma^2_{Empk}$	0.17	0.05	0.16	0.05
% of total σ^2_{mpk}	37.9%	11.5%	35.9%	10.4%
$\sigma^2_{\overline{Empk}}$	0.14	0.05	0.13	0.05
% of total $\sigma^2_{\overline{mpk}}$	47.3%	15.7%	41.9%	15.7%
$\Delta\bar{a}$	0.07	0.02	0.07	0.02
corr $\left(\sigma^2_{Empk_t}, x_t\right)$	-0.31	-0.97	0.45	0.00
Moments				
Er_m	0.08	0.10	0.05	0.06
ESR_m	0.53	0.61	0.52	0.65
corr $\left(\Delta k_t, \Delta k_{t-1}\right)$	0.38	-0.02	0.38	-0.03

of firm-level mpk and the residuals transitory components. We then compute the variance of the permanent component, which yields a value of $\sigma^2_{\overline{mpk}} = 0.30$, about two-thirds of the total.[46] This is the denominator in the fourth row of the table, which displays the model-implied permanent dispersion as a percentage of the observed permanent component in the data. The next row quantifies the implications of the estimated dispersion for the long-run level of aggregate TFP. It reports the gains in the average level of TFP from eliminating this source of mpk dispersion, denoted $\Delta\bar{a}$.[47] This is essentially an application of expression (17).

Column (1) shows that in the full model, risk premium effects lead to mpk dispersion of 0.17. This accounts for about 38% of overall mpk dispersion in the data. Of the model-implied dispersion, about 0.14 is permanent in nature, which explains about 47% of the permanent component in the data. The mpk dispersion arising from risk effects leads to a long-run TFP loss of about 7% (compared to an environment without risk premia, i.e., where $\gamma_0 = \gamma_1 = 0$). These results suggest that (i) variation in firm-level risk exposures can generate significant MPK dispersion, particularly when compared to the permanent component in the data, and (ii) the consequences for measures of aggregate performance such as TFP – i.e., the "productivity costs" of business cycles – can be substantial.

Column (2) shows that on their own (i.e., without adjustment costs), these exposures generate mpk dispersion of 0.05, which accounts for 11.5% of total σ^2_{mpk} in the data and they can explain about 16% of the permanent component. In other words, though the impacts of risk

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[46]Other approaches give a similar breakdown, see, e.g., David and Venkateswaran (2017).

[47]This calculation does not mean that policies eliminating this source of mpk dispersion would necessarily be desirable. We merely see this as a useful way to quantify the implications of our findings.

premia remain significant in isolation, they are less than half of those in column (1). These results highlight the important interactions with other adjustment frictions uncovered in Section 4.3 – in the first column, these effects are taken into account; in the second column, they are not. The associated TFP losses are also smaller, but remain significant, at approximately 2%.

Columns (3) and (4) show that the majority of these effects stems from the presence of a high persistent component in the price of risk, i.e., γ_0, rather than from the time-variation from γ_1. Setting $\gamma_1 = 0$ only modestly reduces the size of these effects in the presence of adjustment costs (compare columns (1) and (3)) and has a negligible effect on the results without them (columns (2) vs. (4)). The implication is that time-varying prices of risk do not add much to the long-run level of mpk dispersion.

Countercyclical dispersion. The last row in the top panel examines the second main implication of the theory, namely, the countercyclicality of mpk dispersion, which we measure as the correlation of $\sigma^2_{Empk_t}$ with the state of the business cycle, i.e., x_t. Column (1) shows that the full model generates significantly countercyclical dispersion in $Empk$ – the correlation of $\sigma^2_{Empk_t}$ with the state of the cycle is -0.31. To put this figure in context, Table 8 in Appendix A.2 shows that the correlation between σ^2_{mpk} and the cyclical component of aggregate productivity in the data is -0.27. Thus, our quantitative model predicts countercyclical dispersion on par with this value. Column (2) shows that as the only factor behind $Empk$ dispersion, the time-varying nature of risk premia would lead to an almost perfectly negative correlation with the business cycle. This is a clear implication of equation (15). The presence of adjustment costs in the first column confounds this relationship and leads to a smaller correlation (in absolute value) that is more in line with the data. Finally, the last two columns illustrate that time-varying risk is key to generating countercyclical dispersion. Without this element, $Empk$ dispersion is significantly positive with adjustment costs and without them, is exactly acyclical. Thus, our findings suggest that the interaction of a countercyclical price of risk with adjustment frictions is crucial in yielding a negative (though far from negative one) correlation between $Empk$ dispersion and the state of the business cycle.

To highlight the potential implications of the countercyclical $Empk$ dispersion produced by our model, consider the connection with the empirical results in Eisfeldt and Rampini (2006), who show that firm-level dispersion measures tend to be countercyclical, yet most capital reallocation is procyclical. Our theory can – at least in part – reconcile this observation due to the countercyclical nature of factor risk prices and the high beta of high MPK firms: countercyclical reallocation would entail moving capital to the riskiest of firms in the riskiest of times. Thus, in light of our results, it may not be as surprising that countercyclical dispersion

obtains, even in a completely frictionless environment.[48]

Moments.   In the bottom panel of Table 7, we investigate the role of each element in matching the target moments. Our full model in column (1) is directly parameterized to match the three moments, i.e., the equity premium, Sharpe ratio and autocorrelation of investment. In column (2), we show these moments from the version of our model without adjustment costs (i.e., setting $\xi = 0$ and the holding the other parameters at their estimated value). As implied by the approximation in Section 4.3, adjustment costs have a modest effect on the properties of returns (eliminating them raises the equity premium somewhat and the Sharpe ratio accordingly). However, the autocorrelation of investment falls dramatically without any adjustment frictions, indeed, becoming slightly negative (due to the mean-reverting nature of shocks). Thus, some degree of adjustment costs is crucial for matching this latter moment. Comparing columns (1) and (3) shows that without time-varying risk, the model struggles to match the equity premium, which falls almost by half, from about 8% to 5%. As implied by expressions (23), (22) and (31), time-varying risk is tightly linked to average excess returns, but has only modest effects on the average Sharpe ratio and the autocorrelation of investment. A similar pattern emerges from columns (2) and (4) – in the absence of adjustment costs, removing time-varying risk significantly reduces the equity premium but has smaller effects on the other two moments.

In sum, the results in Table 7 show first, firm-level variation in risk exposures lead to quantitatively important dispersion in mpk, with significant adverse effects on aggregate TFP; moreover, much of this dispersion is persistent and can account for a significant portion of what seems to be a puzzling pattern in the data, namely, persistent mpk deviations at the firm-level. Second, these risk premium effects add a notably countercyclical element to mpk dispersion, going some way towards reconciling the countercyclical nature of firm-level dispersion measures.

5.3   Other Distortions

Recent work has pointed to a number of additional factors (beyond fundamentals and adjustment frictions) that may affect firms' investment decisions and lead to mpk dispersion, for example, financial frictions or policy-induced distortions. Moreover, it has been pointed out that attempts to identify one of these forces – while abstracting from others – may yield misleading conclusions. This section demonstrates that our strategy of using asset market data is robust to this critique. In other words, our approach yields accurate estimates of risk premium

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[48]The main measure of reallocation in Eisfeldt and Rampini (2006) includes both mergers and acquisitions (M&A) as well as sales of disassembled capital (sales of property, plant and equipment). Even excluding M&A, they find the latter is significantly procyclical (correlation with GDP of about 0.4; data from `https://sites.google.com/site/andrealeisfeldt/home/capital-reallocation-and-liquidity`).

effects, even in the presence of other, un-modeled, distortions.

Rather than take a stand on the exact nature of these factors, we follow the broad literature, e.g., Hsieh and Klenow (2009) and Restuccia and Rogerson (2008), and model these distortions using a flexible class of "taxes" or "wedges," which can have a rich correlation structure over time and with both firm-level characteristics and aggregate conditions (in Section 6 we analyze two additional sources of measured mpk dispersion, namely, heterogeneity in markups and production function parameters). Specifically, we introduce a proportional "tax" on firm-level operating profits, $1 - e^{\tau_{it+1}}$ (so that the firm keeps a portion $e^{\tau_{it+1}}$), of the form:

$$\tau_{it+1} = -\nu_1 z_{it+1} - \nu_2 x_{t+1} - \nu_3 \beta_i x_{t+1} - \eta_{it+1} \ . \tag{26}$$

The first term captures a component correlated with the firm's idiosyncratic productivity, where the strength of the relationship is governed by ν_1. If $\nu_1 > 0$, the wedge discourages (encourages) investment by firms with high (low) idiosyncratic productivity. If $\nu_1 < 0$, the opposite is true. The next two terms capture the correlation of the wedge with the state of the business cycle, x_t. We allow for a component through which all firms are equally distorted by the cyclical portion of the wedge, captured by ν_2, and a component through which high beta firms are disproportionately affected by the cyclical portion, captured by ν_3. Through this piece, the wedge can be correlated with firm-level betas. The last term, η_{it+1}, captures factors that are uncorrelated with firm or aggregate conditions. It can be either time-varying or fixed and is normally distributed with mean zero and variance σ_η^2. Low (high) values of η spur (reduce) investment by firms irrespective of their underlying characteristics or the state of the business cycle.[49] David and Venkateswaran (2017) show that a related formulation describes observed MPK dispersion well (although they do not have beta dispersion or aggregate shocks). We loosely refer to the wedge as a "distortion," although we do not take a stand on whether it stems from efficient factors or not, simply that there are other frictions in the allocation process.

To gain intuition, we analyze each component of the distortion in turn. First, we focus only on the first and last terms, i.e., we set $\nu_2 = \nu_3 = 0$. In this case, the wedge is purely idiosyncratic in the cross-section, i.e., it is always mean zero and has no aggregate component. This formulation is closest to the ones typically used in the literature, which has typically focused on idiosyncratic distortions with no aggregate shocks. Appendix F derives the following expressions for expected mpk and its cross-sectional variance:

$$Empk_{it+1} = \alpha + \nu_1 \rho_z z_{it} + \eta_{it+1} + \beta_i \gamma_t \sigma_\varepsilon^2, \quad \Rightarrow \quad \sigma_{Empk_t}^2 = (\nu_1 \rho_z)^2 \sigma_z^2 + \sigma_\eta^2 + \sigma_\beta^2 \left(\gamma_t \sigma_\varepsilon^2 \right)^2 \ . \tag{27}$$

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[49]We have also studied a version where the distortion is size-dependent, i.e., $\tau_{it+1} = -\nu_k k_{it+1}$. This turns out to be equivalent to the specification in (26) where $\nu_1 = \nu_3 = \frac{\nu_k}{1-\theta+\nu_k}$ and $\nu_2 = 0$.

In this case, $Empk$ includes (i) a component that reflects the correlated distortion, ν_1, and depends on the firm's expectations of its idiosyncratic productivity ($\rho_z z_{it}$), leading to mpk deviations that are correlated with idiosyncratic productivity, and (ii) a term that reflects the uncorrelated distortion, η, which leads to mpk deviations that are uncorrelated with productivity. The last term reflects the risk premium. The second equation in (27) shows that each of these components leads to dispersion in $Empk$ (dispersion in realized mpk also reflects uncertainty over shocks).

Crucially, expression (27) reveals that the risk premium (and resulting risk-based dispersion) are unaffected by the presence of these additional distortions. Further, Appendix F proves that expected stock returns are also unaffected, i.e., equation (20) still holds. The result implies that the mapping from expected returns to beta is, to a first-order, unaffected by the distortions, as is the mapping from beta dispersion to its effects on $Empk$. This leads to an important finding: even in the richer environment here featuring a common class of mis-allocative distortions, using stock market data continues to yield accurate estimates of the effects of heterogeneous risk exposures alone. Clearly, a strategy using mpk dispersion directly does not share this feature: measuring risk effects alone would be complicated by the presence of other distortions.

Next, we add the components that are correlated with aggregate conditions. First, consider the case with a common cyclical component, i.e., $\nu_2 \neq 0$. We can prove a similar result as with only idiosyncratic wedges – the distortion does not affect the cross-sectional dispersion in expected stock returns or the risk-related dispersion in $Empk$.

Finally, consider the case where high beta firms are disproportionately affected by the aggregate distortion, i.e., $\nu_3 \neq 0$. If $\nu_3 > 0$, the distortion discourages (encourages) investment by high (low) beta firms in good times and the reverse in bad times (in this sense, it works like a cyclical productivity-dependent component, since high beta firms are relatively more productive in good times). There is also an aggregate implication of the wedge: averaging across firms gives $\bar{\tau}_{t+1} = -\nu_3 \bar{\beta} x_{t+1}$. If $\nu_3 > 0$ (< 0), the tax is pro- (counter) cyclical. $Empk$ is given by:

$$Empk_{it+1} = \alpha + \nu_1 \rho_z z_{it} + \nu_3 \beta_i \rho_x x_t + (1 - \nu_3) \beta_i \gamma_t \sigma_\varepsilon^2 + \eta_{it+1} \ .$$

The second to last term captures the risk premium, which is now scaled by a factor $1 - \nu_3$. Further, we can show that expected stock returns are scaled by exactly the same factor. What are the implications for our measure of risk-based dispersion in $Empk$? We can prove that expected return dispersion yields a lower bound on risk premium effects if the wedge worsens in downturns, i.e., if $\nu_3 < 0$, which may be a plausible conjecture. On the other hand, we could be at risk of overstating these effects if the wedge is procyclical, i.e., $\nu_3 > 0$. However, even in this case, Appendix F derives an upper bound on ν_3 and shows that any potential bias would

be quantitatively negligible. Intuitively, the bound comes from the fact that observed *Empk* is countercyclical, which limits the scope for a procyclical wedge.

5.4 Directly Measuring Productivity Betas

Our baseline approach to measuring firm-level risk exposures used the link between beta and expected stock returns laid out in Section 4.2. Here, we use an alternative strategy to estimate the dispersion in these exposures using only production-side data. In one sense, this approach is more direct – there is no need to employ firm-level stock market data to measure risk exposures. On the other hand, computing betas directly from production-side data has its drawbacks – the data are of a lower frequency (quarterly at best) and the time dimension of the panel is shorter. Further, it may be difficult to apply this method to firms in developing countries (where measured misallocation tends to be larger), since most firm-level datasets there have relatively short panels and are at the annual frequency. For those reasons, we view our results here as an informative check on our baseline findings above.

The approach is as follows. For each firm, we regress measured productivity growth, i.e., $\Delta z_{it} + \beta_i \Delta x_t$, on aggregate productivity growth Δx_t. It is straightforward to verify that the coefficient from this regression is exactly equal to β_i. Using these estimates, we can compute the firm's underlying productivity beta, $\hat{\beta}_i$, and calculate the cross-sectional dispersion in these estimates, $\sigma_{\hat{\beta}}^2$. We have applied this procedure using three different measures of the aggregate shock: (i) our long sample of Solow residuals, (ii) the series we construct from firm-level data (both of these are described in Appendix A.4) and (iii) the Fernald annual TFP series. The results yield values of $\sigma_{\hat{\beta}}$ of 6.4, 4.3 and 5.9, respectively. Recall that our estimate for this value using stock return data was 4.8, which is in line with – and towards the lower end of – the range found here.

5.5 Measurement Concerns

In this section, we address a number of potential measurement-related issues. First, following the recent literature, e.g., Hsieh and Klenow (2009), Gopinath et al. (2017) and David and Venkateswaran (2017), we measure firm-level capital stocks using reported book values. An alternative approach is to use the perpetual inventory method along with detailed data on investment flows and investment good price deflators to construct capital stocks. Although this is in general an important issue for the firm dynamics/misallocation literatures, our empirical approach allows us to largely avoid this concern. To see this, notice that our estimation relies on measures of firm-level capital in only two places: first, to calculate the properties of idiosyncratic shocks, i.e., ρ_z and $\sigma_{\tilde{\varepsilon}}^2$, and second, to calculate the autocorrelation of investment, which largely

identifies the extent of adjustment costs. As shown, for example, in equations (15) and (21), idiosyncratic shocks have no effect on dispersion in expected mpk or on expected stock returns (the latter to a first-order). In our framework, idiosyncratic risk, though crucial in explaining firm dynamics, is not priced, and thus does not affect risk premia.[50] David and Venkateswaran (2017) measure firm-level capital using both approaches and find a larger serial correlation of investment using the perpetual inventory method. Since our adjustment cost estimate is increasing in the serial correlation, this approach would likely lead to larger estimates, and, as shown above, further amplify the risk premium effects we uncover.[51] Largely avoiding the use of firm-level capital measures is an important feature of our use of stock market data.[52]

How about the effects of measurement error? Our use of stock market data is also useful in this regard – in general, stock market data should be quite precisely measured and so largely free of this concern. Measurement error in capital may affect our estimate of adjustment costs, but we can show that this error would likely lead us to a conservative estimate for these costs. To see this, consider first the case of (classical) measurement error that is iid over time. This unambiguously reduces the observed serial correlation (i.e., the true one is higher), which would yield higher adjustment cost estimates. Alternatively, consider the opposite case where the measurement error is permanent. Then, since we work with the growth rate of capital, our results would be unaffected. Of course, similarly to mis-measured capital, measurement error may affect the observed amount of mpk dispersion.

These issues may also be concerns for our estimates of productivity betas in the previous section, where we used measures of capital to calculate firm-level productivity. However, in Appendix G we show that any potential bias is likely quite small. Loosely speaking, mis-measured capital introduces error into the dependent variable of the regression, which, under certain conditions, will not affect our estimates (specifically, so long as changes in the measurement error are uncorrelated with changes in aggregate productivity). In that appendix we also investigate the potential bias in those estimates coming from unobserved heterogeneity in parameters across firms, i.e., θ, and show that it is quite small.

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[50]We have also verified that idiosyncratic shocks have little effect on our estimates in the full non-linear model (see Appendix H).

[51]If the serial correlation is lower, we can generally think of the results in column 2 of Table 7, where we set adjustment costs to zero, as a lower bound. Although not part of our estimation, we also use firm-level capital to calculate total mpk dispersion, e.g., the denominator in the second row of Table 7. David and Venkateswaran (2017) show that this statistic is very similar under the two meaurement approaches (see Tables 2 and 18 in that paper).

[52]Of course, some of the measured mpk dispersion in the data – i.e., the denominators in rows 2 and 4 of Table 7 may be coming from mis-measurement of capital.

6   What are the Sources of Betas?

Cross-firm variation in exposure to aggregate shocks, i.e., beta, is an essential ingredient in our theory. In this section, we investigate some potential sources of this type of heterogeneity – namely, dispersion in technological parameters (input elasticities in production) and markups as well as in the sensitivity of demand to business cycle fluctuations. Importantly, we show that each of these forms of heterogeneity is reflected in our measured betas, so that our main results on risk premia and mpk dispersion go through unchanged. Our goal here is simply to gain some further insight into why firms exhibit different sensitivities to aggregate shocks.

Heterogeneous technologies/markups.   Firm-level heterogeneity in production function parameters or markups are potential sources of beta dispersion. Intuitively, both of these forces lead firms to have different responsiveness and so exposure to aggregate shocks. In Appendix H, we explore each of these in detail (to allow for markup dispersion, we extend our baseline setup to an environment where firms produce differentiated goods, are monopolistically competitive and face constant, but potentially heterogeneous, elasticities of demand). First, we show that a version of our analysis in Section 4 continues to hold in both cases, where the firm's beta now also reflects these additional sources of heterogeneity. Second, we calculate how much of the observed beta dispersion can be attributed to each of these forces. Using dispersion in labor's share of revenue as a likely upper bound for technology dispersion, we find it can potentially account for about 12% of the overall standard deviation of betas from Section 5. Similarly, using recent estimates of markup dispersion among Compustat firms, we find it can account for about 6%. Thus, in total, heterogeneity in input elasticities and markups are likely to explain at most about 18% of measured beta dispersion. Although this is a significant fraction, these findings also suggest that the majority of beta dispersion seems to arise from other sources.[53]

Heterogeneous demand sensitivities.   A recent literature has pointed out variation in the response of firm-level demand to the business cycle. For example, Jaimovich et al. (2019) document a "trading down" phenomenon – during expansions, when purchasing power is high, households tend to consume higher quality goods and in downturns substitute towards lower quality ones. This pattern makes high quality products more procyclical and lower quality ones less so (or even countercyclical). Similarly, Nevo and Wong (2015) show that during the Great Recession, consumers substituted towards cheaper generic products and discount stores and Coibion et al. (2015) show that during downturns, consumers substitute towards low-price

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[53]Appendix H also investigates potential heterogeneity in the depreciation rate, δ, and the parameters governing idiosyncratic shocks, ρ_z and $\sigma_{\tilde{\varepsilon}}^2$, as well as the effects of adjustment costs alone. We find that these forces are unlikely to account for much of the dispersion in risk premia.

retailers.[54] To see the implications of this pattern for our analysis, consider the following system of demand and production functions:

$$Q_{it} = P_{it}^{-\mu} \left(X_t^{\hat{\beta}_i} \hat{Z}_{it} \right)^{\mu}, \quad Y_{it} = K_{it}^{\hat{\theta}_1} N_{it}^{\hat{\theta}_2} .$$

Here, X_t is interpreted as an aggregate component of demand rather than technology (it is straightforward to include aggregate technology shocks as well) and $\hat{Z}_{it}$ idiosyncratic demand. The firm-specific sensitivity to X_t, $\hat{\beta}_i$, captures the idea that in expansions, when demand for all goods is high, consumers substitute towards some goods and away from others. In downturns, when X_t is low, the opposite pattern holds: consumers substitute away from those same goods. This is a simple way to capture the "trading down" phenomenon. Firm revenues are given by

$$P_{it}Y_{it} = X_t^{\hat{\beta}_i} \hat{Z}_{it} K_{it}^{\theta_1} N_{it}^{\theta_2} ,$$

where $\theta_j = \left(1 - \frac{1}{\mu} \right) \hat{\theta}_j$, $j = 1, 2$. With this reinterpretation, the expression is exactly equivalent to (7). In other words, differences in the responsiveness of firm-level demand to the business cycle may be behind our beta estimates.

Since direct data on quality are hard to come by, systematically quantifying the dispersion in these "demand betas" is challenging. However, we have examined one industry where we were able to obtain a proxy for quality, namely average check per person in SIC 5812, Eating Places (i.e., restaurants). SIC 5812 is defined as "Establishments primarily engaged in the retail sale of prepared food and drinks for on-premise or immediate consumption" and includes food service establishments ranging from fast food (e.g., McDonalds) to high-end restaurants (e.g., Ruth's Chris Steak House). We gathered data (where available) on average check per person (usually proxied by total check divided by the number of entrees ordered) from publicly available sources, including company SEC filings and surveys performed by Citi Research and Morgan Stanley. The data are generally from 2014 to 2015. Matching these prices to the Compustat data yielded a sample of 20 publicly traded firms in SIC 5812 with data on prices, betas, expected returns and MPK (details of data sources and the sample construction are in Appendix H).

Figure 1 illustrates the main results from this exercise. The top two panels of the figure plot average check against CAPM and demand betas, along with the lines of best fit. Both plots show a strong positive relationship – higher quality restaurants, as proxied by price, have higher exposure to aggregate shocks, measured using either stock market or operating data. Firms on the low end include McDonalds (MCD), Burger King (BUR), Wendy's (WEN), Sonic (SON), etc., and towards the higher end Kona Grill (KON), Famous Dave's (FAM) and

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[54]A related literature documents a similar "flight from quality" in response to contractionary exchange rate devaluations. e.g., Burstein et al. (2005), Bems and Di Giovanni (2016) and Chen and Juvenal (2018).

Cheesecake Factory (CHE). The highest-price restaurant in the sample is Ruth's Chris Steak House (RUT).[55] The bottom two panels of the figure go one step further and additionally link quality to measures of expected returns and MPK. Again, there is a strong positive relationship: higher quality restaurants – which the top panel shows tend to be those with higher exposure to aggregate shocks – have higher expected returns and MPK.

In Appendix H we pursue this analysis in further detail and compute the full set of correlations across average check, betas, expected returns and MPK for this set of firms (we also add a measure of beta constructed from the Fama-French factors, which gives similar results). However, Figure 1 neatly summarizes the key message – differences in the responsiveness of firm-level demand to aggregate conditions due to quality variation and "trading down" seems a promising explanation of beta dispersion.
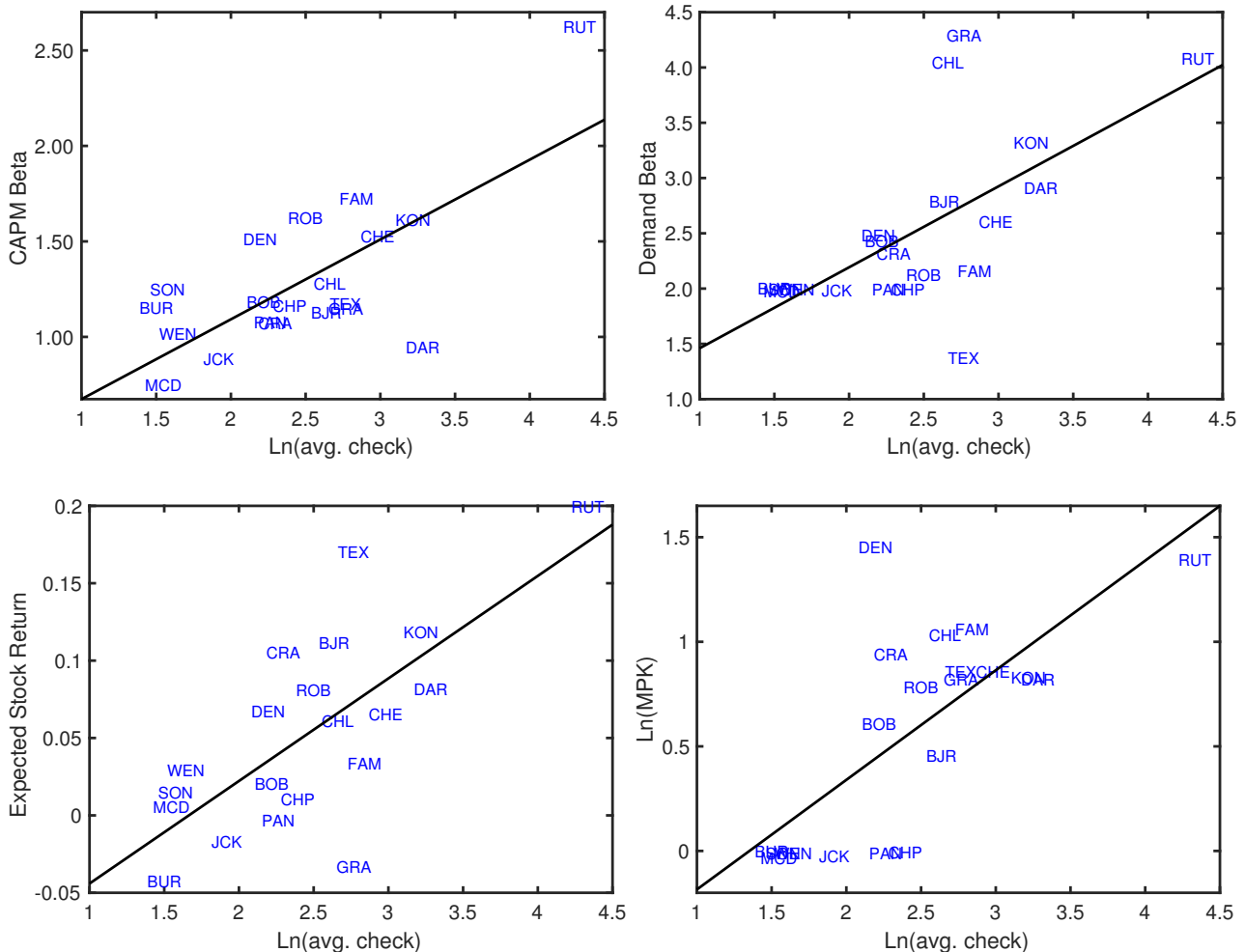

Figure 1: Average Check, Beta, Expected Returns and MPK in SIC 5812, Eating Places

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[55]Ruth's Chris is somewhat of an outlier with a price of $76.00 per person, about three times larger than the next highest. We have verified that omitting Ruth's Chris does not significantly change the results.

7 Conclusion

In this paper, we have revisited the notion of "misallocation" from the perspective of a risk-sensitive, or risk-adjusted, version of the stochastic growth model with heterogeneous firms. The standard optimality condition for investment in this framework suggests that expected firm-level marginal products should reflect exposure to factor risks, and their pricing. To the extent that firms are differentially exposed to these risks, as the literature on cross-sectional asset pricing suggests, the implication is that cross-sectional dispersion in MPK may not only reflect true misallocation, but also risk-adjusted capital allocation. We provide empirical support for this proposition and demonstrate that a suitably parameterized model of firm-level investment behavior suggests that, indeed, risk-adjusted capital allocation accounts for a significant fraction of observed MPK dispersion among US firms. Importantly, much of this dispersion is persistent in nature, which speaks to the large portion of observed MPK dispersion that arises from seemingly persistent/permanent sources. Further, our setup leads to a novel link between aggregate volatility, cross-sectional asset pricing and long-run productivity – our results suggest that there can be substantial "productivity costs" of business cycles.

There are several promising directions for future research. Our framework points to a new connection between business cycle dynamics and the cross-sectional allocation of inputs. Further investigation of this link, for example, a further exploration of the sources of beta variation across firms, would lead to a better understanding of the underlying causes of observed marginal product dispersion. Much of the misallocation literature examines differences in marginal product dispersion across countries. A natural next step would be to implement a similar analysis in a set of developing countries – because those countries typically have high business cycle volatility, it may be that dispersion in risk premia is larger there. The tractability of our setup allowed us to quantify the effects of financial market considerations, e.g., cross-sectional variation in required rates of return, on measures of economic performance, i.e., aggregate TFP. This link provides a new way to evaluate the implications of the rich set of empirical findings in cross-sectional asset pricing. For example, pursuing multifactor/financial shock extensions of our analysis (e.g., along the lines laid out in Appendix E) to incorporate the many risk factors pointed out in that literature would be fruitful to measure the implications of those factors for allocative efficiency. Of particular interest would be whether those factors are efficient or not, e.g., to what extent do capital allocations reflect the "mispricing" of assets.

References

ALVAREZ, F. AND U. J. JERMANN (2004): "Using asset prices to measure the cost of business cycles," *Journal of Political economy*, 112, 1223–1256.

ASKER, J., A. COLLARD-WEXLER, AND J. DE LOECKER (2014): "Dynamic inputs and resource (mis) allocation," *Journal of Political Economy*, 122, 1013–1063.

ATKESON, A. AND P. J. KEHOE (2005): "Modeling and measuring organization capital," *Journal of Political Economy*, 113, 1026–1053.

BALVERS, R. J., L. GU, D. HUANG, M. LEE-CHIN, ET AL. (2015): "Profitability, value and stock returns in production-based asset pricing without frictions," *Journal of Money, Credit, and Banking*.

BARRO, R. J. (2006): "Rare disasters and asset markets in the twentieth century," *The Quarterly Journal of Economics*, 121, 823–866.

BARTELSMAN, E., J. HALTIWANGER, AND S. SCARPETTA (2013): "Cross Country Differences in Productivity: The Role of Allocative Efficiency," *American Economic Review*, 103, 305–334.

BELO, F., X. LIN, AND S. BAZDRESCH (2014): "Labor hiring, investment, and stock return predictability in the cross section," *Journal of Political Economy*, 122, 129–177.

BEMS, R. AND J. DI GIOVANNI (2016): "Income-induced expenditure switching," *American Economic Review*, 106, 3898–3931.

BHARATH, S. T. AND T. SHUMWAY (2008): "Forecasting Default with the Merton Distance to Default Model," *Review of Financial Studies*, 21, 1339–1369.

BINSBERGEN, J. V. AND C. OPP (2017): "Real Anomalies," Wharton Working Paper.

BUERA, F. J., J. P. KABOSKI, AND Y. SHIN (2011): "Finance and Development: A Tale of Two Sectors," *American Economic Review*, 101, 1964–2002.

BURSTEIN, A., M. EICHENBAUM, AND S. REBELO (2005): "Large devaluations and the real exchange rate," *Journal of political Economy*, 113, 742–784.

CHEN, N. AND L. JUVENAL (2018): "Quality and the great trade collapse," *Journal of Development Economics*, 135, 59–76.

COCHRANE, J. (1991): "Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations," *Journal of Finance*, 46, 207–234.

COIBION, O., Y. GORODNICHENKO, AND G. H. HONG (2015): "The cyclicality of sales, regular and effective prices: Business cycle and policy implications," *American Economic Review*, 105, 993–1029.

COOPER, R. W. AND J. C. HALTIWANGER (2006): "On the nature of capital adjustment costs," *The Review of Economic Studies*, 73, 611–633.

DAVID, J. M., E. HENRIKSEN, AND I. SIMONOVSKA (2014): "The risky capital of emerging markets," Tech. rep., National Bureau of Economic Research.

DAVID, J. M., H. A. HOPENHAYN, AND V. VENKATESWARAN (2016): "Information, Misallocation and Aggregate Productivity," *The Quarterly Journal of Economics*, 131, 943–1005.

DAVID, J. M. AND V. VENKATESWARAN (2017): "The Sources of Capital Misallocation," Tech. rep., National Bureau of Economic Research.

DONANGELO, A., F. GOURIO, M. KEHRIG, AND M. PALACIOS (2018): "The cross-section of labor leverage and equity returns," *Journal of Financial Economics*.

EDMOND, C., V. MIDRIGAN, AND D. Y. XU (2018): "How costly are markups?" Tech. rep., National Bureau of Economic Research.

EISFELDT, A. AND A. RAMPINI (2006): "Capital reallocation and liquidity," *Journal of Monetary Economics*, 53, 369–399.

EISFELDT, A. L. AND Y. SHI (2018): "Capital Reallocation," Tech. rep., University of California, Los Angeles.

FAMA, E. F. AND K. R. FRENCH (1992): "Cross-Section of Expected Stock Returns," *The Journal of Finance*, 47, 3247–3265.

FAMA, E. F. AND J. D. MACBETH (1973): "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81, 607–636.

GILCHRIST, S., J. W. SIM, AND E. ZAKRAJŠEK (2013): "Misallocation and financial market frictions: Some direct evidence from the dispersion in borrowing costs," *Review of Economic Dynamics*, 16, 159–176.

GILCHRIST, S. AND E. ZAKRAJSEK (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102, 1692–1720.

GOMES, J. AND L. SCHMID (2010): "Levered Returns," *Journal of Finance*, 65, 467–494.

GOMES, J., A. YARON, AND L. ZHANG (2006): "Asset pricing implications of firms financing constraints," *Review of Financial Studies*, 19, 1321–1356.

GOPINATH, G., Ş. KALEMLI-ÖZCAN, L. KARABARBOUNIS, AND C. VILLEGAS-SANCHEZ (2017): "Capital Allocation and Productivity in South Europe," *The Quarterly Journal of Economics*, 132, 1915–1967.

GUREN, A. M., A. McKAY, E. NAKAMURA, AND J. STEINSSON (2018): "Housing Wealth Effects: The Long View," Tech. rep., Working Paper.

HALTIWANGER, J., R. KULICK, AND C. SYVERSON (2018): "Misallocation measures: The distortion that ate the residual," Tech. rep., National Bureau of Economic Research.

HOPENHAYN, H. A. (2014): "Firms, misallocation, and aggregate productivity: A review," *Annu. Rev. Econ.*, 6, 735–770.

HOU, K., C. XUE, AND L. ZHANG (2015): "Digesting anomalies: An investment approach," *Review of Financial Studies*.

HSIEH, C. AND P. KLENOW (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124, 1403–1448.

İMROHOROĞLU, A. AND Ş. TÜZEL (2014): "Firm-level productivity, risk, and return," *Management Science*, 60, 2073–2090.

JAIMOVICH, N., S. REBELO, AND A. WONG (2019): "Trading down and the business cycle," *Journal of Monetary Economics*.

JONES, C. S. AND S. TUZEL (2013): "Inventory Investment and The Cost of Capital," *Journal of Financial Economics*, 107, 557–579.

KEHRIG, M. (2015): "The Cyclical Nature of the Productivity Distribution," *Working paper*.

KEHRIG, M. AND N. VINCENT (2017): "Do Firms Mitigate or Magnify Capital Misallocation? Evidence from Planet-Level Data," *Working Paper*.

KENNAN, J. (2006): "A note on discrete approximations of continuous distributions," *University of*.

LEWELLEN, J. (2015): "The Cross-section of Expected Stock Returns," *Critical Finance Review*, 4, 1–44.

LEWELLEN, J. AND S. NAGEL (2006): "The conditional CAPM does not explain asset-pricing anomalies," *Journal of Financial Economics*, 82, 289–314.

LIU, L. X., T. M. WHITED, AND L. ZHANG (2009): "Investment-based expected stock returns," *Journal of Political Economy*, 117, 1105–1139.

LUCAS, R. E. (1987): *Models of Business Cycles*, vol. 26, Basil Blackwell Oxford.

MIDRIGAN, V. AND D. Y. XU (2014): "Finance and misallocation: Evidence from plant-level data," *The American Economic Review*, 104, 422–458.

MOLL, B. (2014): "Productivity losses from financial frictions: can self-financing undo capital misallocation?" *The American Economic Review*, 104, 3186–3221.

NEVO, A. AND A. WONG (2015): "The elasticity of substitution between time and market goods: Evidence from the Great Recession," Tech. rep., National Bureau of Economic Research.

NOVY-MARX, R. (2013): "The other side of value: The gross profitability premium," *Journal of Financial Economics*, 108, 1–28.

PETERS, M. (2016): "Heterogeneous Mark-Ups, Growth and Endogenous Misallocation," *Working Paper*.

RESTOY, F. AND M. ROCKINGER (1994): "On Stock Market Returns and Returns on Investment," *Journal of Finance*, 49, 543–556.

RESTUCCIA, D. AND R. ROGERSON (2008): "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments," *Review of Economic Dynamics*, 11, 707–720.

——— (2017): "The causes and costs of misallocation," *Journal of Economic Perspectives*, 31, 151–74.

SHILLER, R. J. (2005): *Irrational Exuberance*, Princeton University Press, 2 ed.

SONG, Z. AND G. L. WU (2015): "Identifying capital misallocation," *Work. Pap., Univ. Chicago, Chicago*.

ZHANG, L. (2005): "The Value Premium," *Journal of Finance*, 60, 67–103.

——— (2017): "The Investment CAPM," *European Financial Management*.

Appendix

A   Data

In this appendix, we describe the various data sources used throughout our analysis.

A.1   Sources and Series Construction

We obtain firm-level data from COMPUSTAT and CRSP. We include firms coded as industrial firms from 1965-2015. Our time-series regressions and portfolio sorts use data from 1973-2015, since data on the GZ spread and EB premium begin in 1973 and because there are relatively few industries with at least 10 firms in a given year pre-1973.[56] We further exclude financial firms by dropping those with COMPUSTAT SIC codes that correspond to finance, insurance, and real estate (FIRE, SIC codes 6000-6999). We also exclude firms with missing SIC codes or coded as non-classifiable, as much of our analysis examines within-industry variables. We measure firm revenue using sales from Compustat (series SALE), and capital using the depreciated value of plant, property, and equipment (series PPENT). We measure firm marginal product of capital in logs (up to an additive constant) as the difference between log revenue and capital, $mpk_{it} = y_{it} - k_{it}$. Market capitalization is measured as the price times shares outstanding from CRSP and profitability as the ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by book assets (AT). We measure market leverage as the ratio of book debt to the sum of market capitalization plus book debt, where book debt is measured as current liabilities (LCT) + 1/2 long term debt (DLTT), following Gilchrist and Zakrajsek (2012). We measure book-to-market as the ratio of book equity to the market capitalization of the firm, where we measure book equity as the sum of shareholder's equity (SEQ), deferred taxes and investment credit (TXDITC) and the preferred stock liquidating value (PSTKL).

We obtain data on aggregate risk factors from the following sources. Data on the Fama-French factors are from Kenneth French's website, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`. Updated data on the price/dividend ratio are from Robert J. Shiller's website, `http://www.econ.yale.edu/~shiller/` and updated measures of the GZ spread and excess bond premium are from Simon Gilchrist's website, `http://people.bu.edu/sgilchri/`.

Computation of betas and expected returns.   Here, we describe our procedure to compute stock market betas, MPK betas and expected returns.

---

[56]The portfolio sorts are qualitatively similar if we use data from the full 1965-2015 sample.

We estimate stock market betas by performing time-series regressions of firm-level excess returns (realized returns from CRSP in excess of the risk-free rate), r^e_{it}, on aggregate factors, denoted by the $N \times 1$ vector $\mathbf{F_t}$. For each firm, the specification takes the form

$$r^e_{it} = \alpha_{i\tau} + \beta_{i\tau}\mathbf{F}_t + \epsilon_{it} \tag{28}$$

We estimate these regressions (and the MPK betas described below) at the quarterly frequency using backwards-looking five-year rolling windows, i.e., for $t \in \{\tau - N_\tau + 1, \tau - \tau_T + 2, ..., \tau\}$, where $\beta_{i\tau}$ denotes the $1 \times N$ vector of factor loadings and N_τ the length of the window.[57] Under the CAPM, the single risk factor is the aggregate market return. Under the Fama-French 3 factor model, the risk factors are the market return (MKT), the return on a portfolio that is long in small firms and short in large ones (SMB) and the return on a portfolio that is long in high book-to-market firms and short on low ones (HML).

To obtain a single measure of risk exposure from the multi-factor Fama-French model, we combine the betas into a single value using estimated prices of risk from Fama and MacBeth (1973) regressions. Specifically, we estimate the following cross-sectional regression in each period:

$$r^e_{it} = \alpha_t + \lambda_t \beta_{it} + \epsilon_{it} \tag{29}$$

where λ_t denotes the $1 \times N$ vector of period t factor risk prices and β_{it} the $N \times 1$ vector of exposures, estimated as just described. We then calculate a single index of exposure to these factors as

$$\beta_{it,FF} = \lambda\beta_{it} = \sum_x \lambda_x \beta_{it,x}, \ x \in MKT, HML, SMB$$

where $\lambda_{\mathbf{x}} = \frac{1}{T}\sum_{t=1}^T \lambda_{\mathbf{x}t}$.

We follow an analogous procedure to estimate MPK betas, simply replacing excess stock market returns on the left-hand side of (28) and (29) with mpk_{it}. The first regression yields measures of β_{MPK}, i.e., the exposure of each firm's MPK to the aggregate risk factors. The second regression combines these exposures into a single value in the multifactor model, using the coefficients from cross-sectional Fama and MacBeth (1973) regressions, which play the role of factor risk prices in determining the relationship between risk exposures and the cross-section of expected MPK.

Finally, we estimate expected stock returns as the predicted values from the cross-sectional asset pricing equation

$$r^e_{it} = \alpha_i + \lambda\beta_{it} + \varepsilon_{it}$$

---

[57]We have also estimated the stock market betas using higher frequency monthly data (and two-year rolling windows) and obtained similar results.

i.e., as $\alpha_i + \lambda\beta_{it}$, where β_{it} is as estimated from equation (28), λ is calculated using the estimates from (29) as described above, and α_i is calculated as $\alpha_i = \frac{1}{T}\sum_{t=1}^{T}(\alpha_{it} + \epsilon_{it})$ also using the estimates from (29).

Composition-adjusted measures of mean and dispersion. For Predictions 2 and 4, we compute time-series of the mean and cross-sectional dispersion in MPK. Because Compustat is an unbalanced panel with significant changes in the composition of firms over time, it is important to ensure that we measure the variation in these objects due to changes in firm MPK, rather than additions or deletions from the dataset (especially since many additions and deletions to the Compustat data may not be true firm entry or exit). We therefore compute composition-adjusted measures of the mean and cross-sectional standard deviation in MPK that are only affected by firms who continue on in the dataset. We use the following procedure:

For each set of adjacent periods, e.g., t and $t+1$, we compute the statistic of interest in each time period (i.e., mean or cross-sectional standard deviation) only for those firms that are present in the data in both periods. Taking the difference yields the change in the statistic from time t to $t+1$ that is due only to changes in the common set of firms. Completing this procedure yields time-series of changes in the mean and cross-sectional standard deviation of MPK. We then combine these time-series of changes with the initial values of the statistics of interest (across all firms in the initial period) to construct a synthetic series for each statistic, which is not affected by the changing composition of firms in the data.

A.2   Time-Series Correlations

Table 8 reports contemporaneous correlations between (within-industry) MPK dispersion and indicators of the price of risk and the business cycle.

A.3   Expected Return Distribution

Table 9 reports statistics from the cross-sectional distribution of expected returns ($E[r^e]$) and unlevered expected returns ($E[r^a]$), which is a measure of expected asset returns. We de-lever expected returns using an adjustment factor computed from Black-Scholes following the approach in, e.g., Bharath and Shumway (2008) and Gilchrist and Zakrajsek (2012). Specifically, we implement an iterative procedure using data on realized equity volatility, firm debt, and firm market capitalization to compute the implied value of assets and asset volatility. The Black-Scholes equations imply $\mathbb{E}[r^a] \approx \frac{Mkt.\ cap.}{V_A}\Phi(\delta_1)\mathbb{E}[r^e]$, where V_A is the total firm asset value implied by Black-Scholes as a function of the market capitalization of equity, book debt, and realized backwards-looking equity volatility and $\Phi(\delta_1)$ is the Black-Scholes "delta" of eq-

Table 8: Correlations of MPK Dispersion, the Price of Risk and the Business Cycle

	MPK Dispersion	PD Ratio	GZ Spread	EB Premium	GDP	TFP
MPK Dispersion	1.00					
PD Ratio	-0.42	1.00				
GZ Spread	0.39	-0.51	1.00			
EB Premium	0.51	-0.57	0.68	1.00		
GDP	-0.53	0.46	-0.59	-0.66	1.00	
TFP	-0.27	0.43	-0.32	-0.44	0.70	1.00

Notes: This table reports time-series correlations of MPK dispersion, measures of the price of risk and the business cycle. MPK dispersion is measured as the within-industry standard deviation in *mpk*. The PD ratio is the aggregate stock market price/dividend ratio. The GZ spread and EB (excess bond) premium are measures of credit spreads. GDP is log GDP and TFP is log TFP. We extract the cyclical components of GDP, TFP and the PD ratio using a one-sided Hodrick-Prescott filter. All series are described in more detail in the main text and Appendix A.1. All data are quarterly and are from 1973-2015.

uity, as defined in, e.g., Gilchrist and Zakrajsek (2012). We compute the adjustment factor $\frac{Mkt.\ cap.}{V^A}\Phi(\delta_1)$ for each firm using daily data and a 21 day backwards-looking window for equity volatility and then calculate a firm-year adjustment factor by averaging this adjustment factor for each firm-year. Finally, we compute un-levered expected returns for each firm as the product of its expected equity return multiplied by this factor. To find the cross-sectional distribution of within-industry expected returns, we de-mean expected returns by industry-year, keeping industry-years with at least 10 observations. We then add back the means and report the resulting distribution.[58] Figure 2 plots the full cross-sectional distribution of within-industry expected excess asset and equity returns.

Table 9: The Distribution of Expected Excess Returns

Percentile	10th	25th	Mean	75th	90th	Std. Dev.
	Panel A: Not Industry-Adjusted					
$E[r^a]$	-3.6%	4.0%	9.8%	17.1%	24.7%	13.2%
$E[r^e]$	-5.3%	6.6%	12.1%	20.6%	28.6%	15.6%
	Panel B: Industry-Adjusted					
$E[r^a]$	-3.6%	4.7%	9.8%	16.6%	23.6%	12.7%
$E[r^e]$	-4.6%	6.6%	12.1%	20.3%	28.1%	15.0%

Notes: This table reports the cross-sectional distributions of un-levered expected excess equity returns, $E[r^a]$, and expected excess equity returns, $E[r^e]$. Industry adjustment is done by demeaning each measure of expected returns by industry-year. We then add back the mean returns to these distributions.

---

[58]The results are similar if we compute our cross-sectional statistics within each year or industry-year and average over the years/industry-years
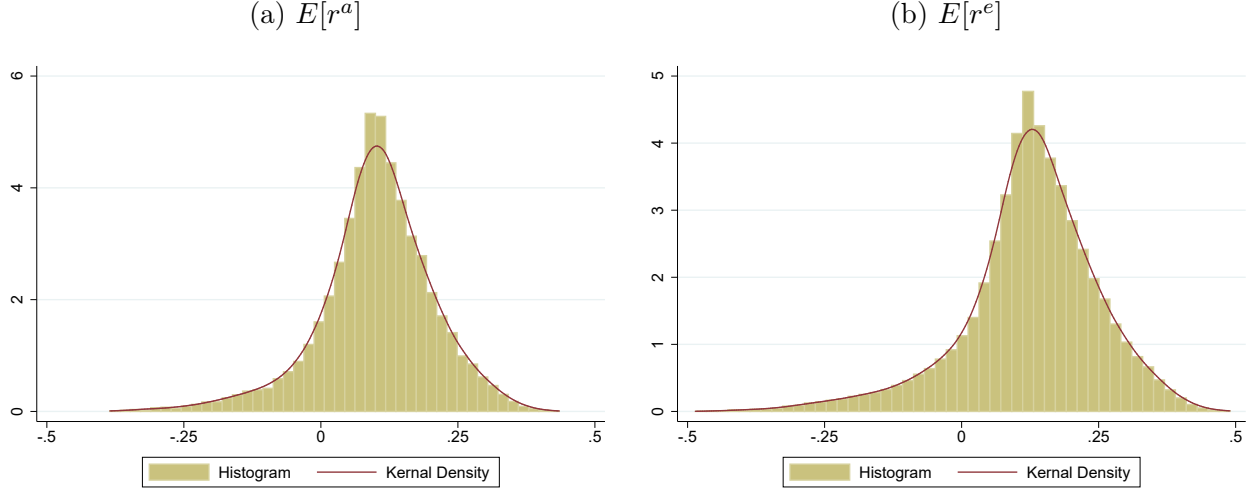
Figure 2: Cross-Sectional Distribution of Expected Excess Returns

Notes: This figure displays the cross-sectional distributions of un-levered expected excess equity returns, $E[r^a]$, and expected excess equity returns, $E[r^e]$. Industry adjustment is done by demeaning each measure of expected returns by industry-year. We then add back the mean returns to these distributions. The vertical bars denote the histograms of these distributions, while the solid lines are the results of kernel smoothing regressions with a bandwidth of 0.25.

A.4 Aggregate Productivity Series

Solow residuals. To build a series of Solow residuals, we obtain data on real GDP and aggregate labor and capital from the Bureau of Economic Analysis. Data on real GDP are from BEA Table 1.1.3 ("Real Gross Domestic Product"), data on labor are from BEA Table 6.4 ("Full-Time and Part-Time Employees") and data on the capital stock are from BEA Table 1.2 ("Net Stock of Fixed Assets"). The data are available annually from 1929-2016. With these data we compute $x_t = y_t - \theta_1 k_t - \theta_2 n_t$. We extract a linear time-trend and then estimate the autoregression in equation (8).

Firm-level series. To construct the alternative series for aggregate productivity from the firm-level data, we use the following procedure. First, we compute firm-level productivity as $z_{it} + \beta_i x_t = y_{it} - \theta k_{it}$. We then average these values across all firms in each year. Because z_{it} is mean-zero and independent across firms, this yields a scaled measure of aggregate productivity, $\bar{\beta} x_t$, where $\bar{\beta}$ is the mean beta across firms, which under our assumptions, is approximately two. We extract a linear time-trend from this series and then estimate the autoregression. The coefficient from this regression gives ρ_x. The standard deviations of the residuals gives $\bar{\beta}\sigma_\varepsilon$ and after dividing by $\bar{\beta}$ gives the true volatility of shocks. Applying this procedure to the set of Compustat firms over the period 1962-2016 yields values of $\rho_x = 0.92$ and $\sigma_\varepsilon = .0245$.

51

B   Motivation

Derivation of equation (3).

$$
\begin{aligned}
1 &= \mathbb{E}_t \left[M_{t+1} \left(MPK_{it+1} + 1 - \delta \right) \right] \\
&= \mathbb{E}_t \left[M_{t+1} \right] \mathbb{E}_t \left[MPK_{it+1} + 1 - \delta \right] + \mathrm{cov} \left(M_{t+1}, MPK_{it+1} \right)
\end{aligned}
$$

Consider the MPK of a 'risk-free' firm defined by $\mathrm{cov} \left(M_{t+1}, MPK_{ft+1} \right) = 0$. We have

$$
1 = \mathbb{E}_t \left[M_{t+1} \right] \left(MPK_{ft+1} + 1 - \delta \right)
$$

and combining,

$$
\begin{aligned}
\mathbb{E}_t \left[MPK_{it+1} \right] &= MPK_{ft+1} - \frac{\mathrm{cov} \left(M_{t+1}, MPK_{it+1} \right)}{\mathbb{E}_t \left[M_{t+1} \right]} \\
&= \alpha_t + \beta_{it} \lambda_t
\end{aligned}
$$

where α_t, β_{it} and λ_t are as defined in the text.. By a no-arbitrage condition, it must be the case that $\frac{1}{\mathbb{E}_t[M_{t+1}]} = MPK_{ft+1} + 1 - \delta = R_{ft}$ where R_{ft} is the gross risk-free interest rate.

No aggregate risk.   With no aggregate risk, $M_{t+1} = \rho \; \forall \, t$ where ρ is the rate of time discount. The Euler equation gives

$$
1 = \rho \left(\mathbb{E}_t \left[MPK_{it+1} \right] + 1 - \delta \right) \; \forall \, i, t \quad \Rightarrow \quad \mathbb{E}_t \left[MPK_{it+1} \right] = \frac{1}{\rho} - (1 - \delta) = r_f + \delta
$$

CAPM.   Clearly, $-\mathrm{cov} \left(M_{t+1}, MPK_{it+1} \right) = b\,\mathrm{cov} \left(r_{mt+1}, MPK_{it+1} \right)$ and $\mathrm{var} \left(M_{t+1} \right) = b^2 \mathrm{var} \left(r_{mt+1} \right)$. Since the market return is an asset, it must satisfy $\mathbb{E}_t \left[r_{mt+1} \right] = r_{ft} + \frac{\lambda_t}{b}$ so that $\lambda_t = b \left(\mathbb{E}_t \left[r_{mt+1} \right] - r_{ft} \right)$. Substituting into expression (3) gives the CAPM expression in the text.

CCAPM.   A log-linear approximation to the SDF around its unconditional mean gives $M_{t+1} \approx \mathbb{E} \left[M_{t+1} \right] \left(1 + m_{t+1} - \mathbb{E} \left[m_{t+1} \right] \right)$ and in the case of $CRRA$ utility, $m_{t+1} = -\gamma \Delta c_{t+1}$ where Δc_{t+1} is log consumption growth. Substituting for M_{t+1} into expression (3) gives the CCAPM expression in the text.

C   Baseline Model

This appendix provides detailed derivations for the baseline model and analysis.

C.1 Solution – No Adjustment Costs

The static labor choice solves

$$\max e^{\hat{z}_{it}+\hat{\beta}_i x_t} K_{it}^{\theta_1} N_{it}^{\theta_2} - W_t N_{it}$$

with the associated first order condition

$$N_{it} = \left(\frac{\theta_2 e^{\hat{z}_{it}+\hat{\beta}_i x_t} K_{it}^{\theta_1}}{W_t} \right)^{\frac{1}{1-\theta_2}}$$

Substituting for the wage with $W_t = X_t^\omega$ and rearranging gives operating profits

$$\Pi_{it} = G e^{\beta_i x_t + z_{it}} K_{it}^\theta$$

where $G \equiv (1-\theta_2)\theta_2^{\frac{\theta_2}{1-\theta_2}}$, $\beta_i = \frac{1}{1-\theta_2}\left(\hat{\beta}_i - \omega\theta_2\right)$, $z_{it} = \frac{1}{1-\theta_2}\hat{z}_{it}$ and $\theta = \frac{\theta_1}{1-\theta_2}$, which is equation (10) in the text.

The first order and envelope conditions associated with (1) give the Euler equation:

$$
\begin{aligned}
1 &= \mathbb{E}_t \left[M_{t+1} \left(\theta e^{z_{it+1}+\beta_i x_{t+1}} G K_{it+1}^{\theta-1} + 1 - \delta \right) \right] \\
&= (1-\delta) \mathbb{E}_t \left[M_{t+1} \right] + \theta G K_{it+1}^{\theta-1} \mathbb{E}_t \left[e^{m_{t+1}+z_{it+1}+\beta_i x_{t+1}} \right]
\end{aligned}
$$

Substituting for m_{t+1} and rearranging,

$$
\begin{aligned}
\mathbb{E}_t \left[e^{m_{t+1}+z_{it+1}+\beta_i x_{t+1}} \right] &= \mathbb{E}_t \left[e^{\log\rho - \gamma_t \varepsilon_{t+1} - \frac{1}{2}\gamma_t^2\sigma_\varepsilon^2 + z_{it+1}+\beta_i x_{t+1}} \right] \\
&= \mathbb{E}_t \left[e^{\log\rho + \rho_z z_{it} + \varepsilon_{it+1} + \beta_i \rho_x x_t + (\beta_i-\gamma_t)\varepsilon_{t+1} - \frac{1}{2}\gamma_t^2\sigma_\varepsilon^2} \right] \\
&= e^{\log\rho + \rho_z z_{it} + \beta_i \rho_x x_t + \frac{1}{2}\sigma_{\tilde{\varepsilon}}^2 + \frac{1}{2}\beta_i^2\sigma_\varepsilon^2 - \beta_i\gamma_t\sigma_\varepsilon^2}
\end{aligned}
$$

and

$$\mathbb{E}_t \left[M_{t+1} \right] = \mathbb{E}_t \left[e^{\log\rho - \gamma_t\varepsilon_{t+1} - \frac{1}{2}\gamma_t^2\sigma_\varepsilon^2} \right] = e^{\log\rho + \frac{1}{2}\gamma_t^2\sigma_\varepsilon^2 - \frac{1}{2}\gamma_t^2\sigma_\varepsilon^2} = \rho$$

so that

$$\theta G K_{it+1}^{\theta-1} = \frac{1 - (1-\delta)\rho}{e^{\log\rho + \rho_z z_{it} + \beta_i \rho_x x_t + \frac{1}{2}\sigma_{\tilde{\varepsilon}}^2 + \frac{1}{2}\beta_i^2\sigma_\varepsilon^2 - \beta_i\gamma_t\sigma_\varepsilon^2}}$$

and rearranging and taking logs,

$$k_{it+1} = \frac{1}{1-\theta}\left(\tilde{\alpha} + \frac{1}{2}\sigma_{\tilde{\varepsilon}}^2 + \frac{1}{2}\beta_i^2\sigma_\varepsilon^2 + \rho_z z_{it} + \beta_i\rho_x x_t - \beta_i\gamma_t\sigma_\varepsilon^2 \right)$$

where

$$\tilde{\alpha} = \log\theta + \log G - \alpha$$

$$\alpha = -\log\rho + \log\left(1 - (1-\delta)\rho\right) = r_f + \log\left(1 - (1-\delta)\rho\right)$$

Ignoring the variance terms gives equation (11).

The realized mpk is given by

$$
\begin{aligned}
mpk_{it+1} &= \log\theta + \pi_{it+1} - k_{it+1} \\
&= \log\theta + \log G + z_{it+1} + \beta_i x_{t+1} - (1-\theta)k_{it+1} \\
&= \log\theta + \log G + z_{it+1} + \beta_i x_{t+1} - \tilde{\alpha} - \rho_z z_{it} - \beta_i \rho_x x_t + \beta_i \gamma_t \sigma_\varepsilon^2 \\
&= \alpha + \varepsilon_{it+1} + \beta_i \varepsilon_{t+1} + \beta_i \gamma_t \sigma_\varepsilon^2
\end{aligned}
$$

The time t conditional expected mpk is

$$\mathbb{E}_t\left[mpk_{it+1}\right] = \alpha + \beta_i \gamma_t \sigma_\varepsilon^2$$

and the time t and mean cross-sectional variances are, respectively,

$$
\begin{aligned}
\sigma^2_{\mathbb{E}_t[mpk_{it+1}]} &= \sigma_\beta^2 \left(\gamma_t \sigma_\varepsilon^2\right)^2 \\
\mathbb{E}\left[\sigma^2_{\mathbb{E}_t[mpk_{it+1}]}\right] &= \mathbb{E}\left[\sigma_\beta^2\left(\gamma_0 + \gamma_1 x_t\right)^2\left(\sigma_\varepsilon^2\right)^2\right] = \sigma_\beta^2\left(\gamma_0^2 + \gamma_1^2 \sigma_x^2\right)\left(\sigma_\varepsilon^2\right)^2
\end{aligned}
$$

C.2 Solution – Adjustment Costs

With capital adjustment costs, the firm's investment problem takes the form

$$
\begin{aligned}
V\left(X_t, Z_{it}, K_{it}\right) = \max_{K_{it+1}} \quad & G X_t^{\beta_i} Z_t K_{it}^{\theta} - K_{it+1} + (1-\delta)K_{it} - \Phi\left(I_{it}, K_{it}\right) \tag{30} \\
+ \ & \mathbb{E}_t\left[M_{t+1} V\left(X_{t+1}, Z_{it+1}, K_{it+1}\right)\right]
\end{aligned}
$$

Policy function. The first order and envelope conditions associated with (30) give the Euler equation:

$$
\begin{aligned}
1 + \xi\left(\frac{K_{it+1}}{K_{it}} - 1\right) &= \mathbb{E}_t\left[M_{t+1}\left(G\theta e^{z_{it+1}+\beta_i x_{t+1}} K_{it+1}^{\theta-1} + 1 - \delta - \frac{\xi}{2}\left(\frac{K_{it+2}}{K_{it+1}} - 1\right)^2 + \xi\left(\frac{K_{it+2}}{K_{it+1}} - 1\right)\frac{K_{it+2}}{K_{it+1}}\right)\right] \\
&= \mathbb{E}_t\left[M_{t+1}\left(G\theta e^{z_{it+1}+\beta_i x_{t+1}} K_{it+1}^{\theta-1} + 1 - \delta + \frac{\xi}{2}\left(\frac{K_{it+2}}{K_{it+1}}\right)^2 - \frac{\xi}{2}\right)\right]
\end{aligned}
$$

In the non-stochastic steady state,

$$
\begin{aligned}
MPK &= G\theta K^{\theta-1} = \frac{1}{\rho} + \delta - 1 \quad \Rightarrow \quad K = \left[\frac{1}{G\theta}\left(\frac{1}{\rho} + \delta - 1\right)\right]^{\frac{1}{\theta-1}} \\
\Pi &= GK^{\theta} \quad \Rightarrow D = GK^{\theta} - \delta K \\
P &= \frac{\rho}{1-\rho}D \\
R &= 1 + \frac{D}{P} = \frac{1}{\rho} \quad \Rightarrow r_f = -\log\rho
\end{aligned}
$$

Define the investment return:

$$
R_{it+1}^{I} = \frac{G\theta e^{z_{it+1}+\beta_i x_{it+1}} K_{it+1}^{\theta-1} + 1 - \delta + \frac{\xi}{2}\left(\frac{K_{it+2}}{K_{it+1}}\right)^2 - \frac{\xi}{2}}{1 + \xi\left(\frac{K_{it+1}}{K_{it}} - 1\right)}
$$

and log-linearizing,

$$
\begin{aligned}
r_{it+1}^{I} &= \rho G\theta K^{\theta-1}\left(z_{it+1} + \beta_i x_{t+1}\right) + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)k_{it+1} + \rho\xi k_{it+2} + \xi k_{it} \\
&- \log\rho - \rho G\theta\left(\theta-1\right)K^{\theta-1}k
\end{aligned}
$$

where $k = \log K$.

To derive the investment policy function, conjecture it takes the form

$$
k_{it+1} = \phi_{0i} + \phi_1\beta_i x_t + \phi_2 z_{it} + \phi_3 k_{it}
$$

Then,

$$
k_{it+2} = \phi_{0i}\left(1 + \phi_3\right) + \phi_1\beta_i\left(\rho_x + \phi_3\right)x_t + \phi_2\left(\rho_z + \phi_3\right)z_{it} + \phi_3^2 k_{it} + \phi_1\beta_i\varepsilon_{t+1} + \phi_2\varepsilon_{it+1}
$$

Substituting into the investment return,

$$
\begin{aligned}
r_{it+1}^{I} &= \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1 - \rho\phi_3\right)\right)\phi_{0i} - \log\rho - \rho G\theta\left(\theta-1\right)K^{\theta-1}k \\
&+ \left(\rho G\theta K^{\theta-1}\rho_z + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_2 + \rho\xi\left(\rho_z + \phi_3\right)\phi_2\right)z_{it} \\
&+ \left(\rho G\theta K^{\theta-1}\rho_x + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_1 + \rho\xi\left(\rho_x + \phi_3\right)\phi_1\right)\beta_i x_t \\
&+ \left(\left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_3 + \rho\xi\phi_3^2 + \xi\right)k_{it} \\
&+ \left(\rho G\theta K^{\theta-1} + \rho\xi\phi_2\right)\varepsilon_{it+1} + \left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)\beta_i\varepsilon_{t+1}
\end{aligned}
$$

and

$$
\begin{aligned}
r^I_{it+1} + m_{it+1} ={}& \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1-\rho\phi_3\right)\right)\phi_{0i} - \rho G\theta\left(\theta-1\right)K^{\theta-1}k - \frac{1}{2}\gamma_0^2\sigma_\varepsilon^2 - \frac{1}{2}\gamma_1^2\sigma_\varepsilon^2 x_t^2 \\
&+ \left(\rho G\theta K^{\theta-1}\rho_z + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_2 + \rho\xi\left(\rho_z+\phi_3\right)\phi_2\right)z_{it} \\
&+ \left(\left(\rho G\theta K^{\theta-1}\rho_x + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_1 + \rho\xi\left(\rho_x+\phi_3\right)\phi_1\right)\beta_i - \gamma_0\gamma_1\sigma_\varepsilon^2\right)x_t \\
&+ \left(\left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_3 + \rho\xi\phi_3^2 + \xi\right)k_{it} \\
&+ \left(\rho G\theta K^{\theta-1} + \rho\xi\phi_2\right)\varepsilon_{it+1} + \left(\left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)\beta_i - \gamma_0 - \gamma_1 x_t\right)\varepsilon_{t+1}
\end{aligned}
$$

The Euler equation governing the investment return implies

$$
\begin{aligned}
0 ={}& \mathbb{E}_t\left[r^I_{it+1} + m_{t+1}\right] + \frac{1}{2}\mathrm{var}\left(r^I_{it+1} + m_{it+1}\right) \\
={}& \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1-\rho\phi_3\right)\right)\phi_{0i} - \rho G\theta\left(\theta-1\right)K^{\theta-1}k \\
&+ \left(\rho G\theta K^{\theta-1}\rho_z + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_2 + \rho\xi\left(\rho_z+\phi_3\right)\phi_2\right)z_{it} \\
&+ \left(\rho G\theta K^{\theta-1}\rho_x + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_1 + \rho\xi\left(\rho_x+\phi_3\right)\phi_1 - \left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)\gamma_1\sigma_\varepsilon^2\right)\beta_i x_t \\
&+ \left(\left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_3 + \rho\xi\phi_3^2 + \xi\right)k_{it} \\
&+ \frac{1}{2}\left(\rho G\theta K^{\theta-1} + \rho\xi\phi_2\right)^2\sigma_{\tilde\varepsilon}^2 \\
&+ \frac{1}{2}\left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)^2\beta_i^2\sigma_\varepsilon^2 - \left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)\beta_i\gamma_0\sigma_\varepsilon^2
\end{aligned}
$$

and we can solve for the coefficients from:

$$
\begin{aligned}
0 ={}& \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1-\rho\phi_3\right)\right)\phi_{0i} - \rho G\theta\left(\theta-1\right)K^{\theta-1}k \\
&+ \frac{1}{2}\left(\rho G\theta K^{\theta-1} + \rho\xi\phi_2\right)^2\sigma_{\tilde\varepsilon}^2 \\
&+ \frac{1}{2}\left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)^2\beta_i^2\sigma_\varepsilon^2 - \left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)\beta_i\gamma_0\sigma_\varepsilon^2 \\
={}& \rho G\theta K^{\theta-1}\rho_z + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_2 + \rho\xi\left(\rho_z+\phi_3\right)\phi_2 \\
={}& \rho G\theta K^{\theta-1}\rho_x + \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_1 + \rho\xi\left(\rho_x+\phi_3\right)\phi_1 - \left(\rho G\theta K^{\theta-1} + \rho\xi\phi_1\right)\gamma_1\sigma_\varepsilon^2 \\
={}& \left(\rho G\theta\left(\theta-1\right)K^{\theta-1} - \xi\left(1+\rho\right)\right)\phi_3 + \rho\xi\phi_3^2 + \xi
\end{aligned}
$$

Define $\hat{\xi} = \frac{\xi}{\rho G \theta K^{\theta-1}} = \frac{\xi}{1-\rho(1-\delta)}$. Then,

$$0 = \left((\theta - 1) - \hat{\xi}(1 + \rho)\right)\phi_3 + \rho\hat{\xi}\phi_3^2 + \hat{\xi}$$

$$\phi_1 = \frac{(\rho_x - \gamma_1\sigma_\varepsilon^2)\phi_3}{\hat{\xi}(1 - \rho\rho_x\phi_3 + \rho\gamma_1\sigma_\varepsilon^2\phi_3)}$$

$$\phi_2 = \frac{\rho_z\phi_3}{\hat{\xi}(1 - \rho\rho_z\phi_3)}$$

$$\phi_{0i} = \phi_{00} - \phi_{01}\beta_i + \phi_{02}\beta_i^2$$

where

$$\phi_{00} = \frac{\rho G\theta(1-\theta)K^{\theta-1}k + \frac{1}{2}\left(\rho G\theta K^{\theta-1} + \rho\xi\phi_2\right)^2\sigma_{\tilde\varepsilon}^2}{\rho G\theta(1-\theta)K^{\theta-1} + \xi(1 - \rho\phi_3)}$$

$$\phi_{01} = \frac{\phi_3}{\hat{\xi}(1 - \rho\phi_3)}\frac{\gamma_0\sigma_\varepsilon^2}{1 - \rho\rho_x\phi_3 + \rho\gamma_1\sigma_\varepsilon^2\phi_3}$$

$$\phi_{02} = \frac{\rho G\theta K^{\theta-1}\rho\xi\phi_1 + \frac{1}{2}(\rho\xi\phi_1)^2 + \frac{1}{2}\left(\rho G\theta K^{\theta-1}\right)^2}{\rho G\theta(1-\theta)K^{\theta-1} + \xi(1 - \rho\phi_3)}\sigma_\varepsilon^2$$

Note that $\frac{\phi_3}{\hat{\xi}}$ goes to $\frac{1}{1-\theta}$ as $\hat{\xi}$ goes to zero and zero as $\hat{\xi}$ goes to infinity. Again ignoring variance terms, the policy function is

$$k_{it+1} = \phi_{00} + \phi_1\beta_i x_t + \phi_2 z_{it} + \phi_3 k_{it} - \phi_{01}\beta_i$$

which is equation (24) in the text.

MPK Dispersion. The expected mpk is given by

$$\mathbb{E}_t[mpk_{it+1}] = \log\theta + \log G + \beta_i\rho_x x_t + \rho_z z_{it} - (1-\theta)k_{it+1}$$

and the mean of this is

$$\mathbb{E}[\mathbb{E}_t[mpk_{it+1}]] = \log\theta + \log G - (1-\theta)\mathbb{E}[k_{it+1}]$$

From the policy function,

$$\mathbb{E}[k_{it+1}] = \frac{\phi_{00} - \phi_{01}\beta_i}{1 - \phi_3}$$

so that

$$\mathbb{E}[\mathbb{E}_t[mpk_{it+1}]] = \log\theta + \log G - \frac{1-\theta}{1-\phi_3}(\phi_{00} - \phi_{01}\beta_i)$$

and the variance of this permanent component is

$$\sigma^2_{\mathbb{E}[\mathbb{E}_t[mpk_{it+1}]]} = \left(\frac{1-\theta}{1-\phi_3}\right)^2 \phi^2_{01}\sigma^2_\beta$$

which is equation (25) in the text.

C.3   Aggregation

The first order condition on labor gives

$$N_{it} = \left(\frac{\theta_2 e^{\hat{\beta}_i x_t + \hat{z}_{it}} K_{it}^{\theta_1}}{W_t}\right)^{\frac{1}{1-\theta_2}}$$

and substituting for the wage,

$$N_{it} = \left(\theta_2 e^{(\hat{\beta}_i - \omega)x_t + \hat{z}_{it}} K_{it}^{\theta_1}\right)^{\frac{1}{1-\theta_2}}$$

Labor market clearing gives:

$$N_t = \int N_{it} di = \theta_2^{\frac{1}{1-\theta_2}} e^{-\frac{1}{1-\theta_2}\omega x_t} \int e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta} di$$

so that

$$\theta_2^{\frac{\theta_2}{1-\theta_2}} e^{-\frac{\theta_2}{1-\theta_2}\omega x_t} = \left(\frac{N_t}{\int e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta} di}\right)^{\theta_2}$$

Then,

$$\begin{aligned}
Y_{it} &= e^{\hat{\beta}_i x_t + \hat{z}_{it}} K_{it}^{\theta_1} N_{it}^{\theta_2} = \theta_2^{\frac{\theta_2}{1-\theta_2}} e^{-\frac{\theta_2}{1-\theta_2}\omega x_t} e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta} \\
&= \frac{e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta}}{\left(\int e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta} di\right)^{\theta_2}} N_t^{\theta_2}
\end{aligned}$$

By definition,

$$MPK_{it} = \frac{\theta e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta-1}}{\left(\int e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta} di\right)^{\theta_2}} N_t^{\theta_2}$$

and rearranging,

$$K_{it} = \left(\frac{\theta e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}}}{MPK_{it}} \right)^{\frac{1}{1-\theta}} \left(\frac{N_t}{\int e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta} di} \right)^{\frac{\theta_2}{1-\theta}}$$

Capital market clearing gives

$$K_t = \int K_{it} di = \theta^{\frac{1}{1-\theta}} \left(\frac{N_t}{\int e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} K_{it}^{\theta} di} \right)^{\frac{\theta_2}{1-\theta}} \int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di$$

so that

$$K_{it}^{\theta} = \left(\frac{e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}}}{\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di} K_t \right)^{\theta}$$

and substituting into the expression for Y_{it},

$$
Y_{it} = \frac{e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} \left(\dfrac{e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}}}{\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di} K_t \right)^{\theta}}{\left(\int e^{\frac{1}{1-\theta_2}\hat{\beta}_i x_t + z_{it}} \left(\dfrac{e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}}}{\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di} K_t \right)^{\theta} di \right)^{\theta_2}} N_t^{\theta_2}
$$

$$
= \frac{\dfrac{e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{\theta}{1-\theta}}}{\left(\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di \right)^{\theta}}}{\left(\dfrac{\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{\theta}{1-\theta}} di}{\left(\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di \right)^{\theta}} \right)^{\theta_2}} K_t^{\theta_1} N_t^{\theta_2}
$$

Aggregate output is then

$$Y_t = \int Y_{it} di = A_t K_t^{\theta_1} N_t^{\theta_2}$$

where

$$A_t = \left(\frac{\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{\theta}{1-\theta}} di}{\left(\int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta} z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di \right)^{\theta}} \right)^{1-\theta_2}$$

Taking logs,

$$a_t = (1-\theta_2)\left(\log \int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta}z_{it}} MPK_{it}^{-\frac{\theta}{1-\theta}} di - \theta \log \int e^{\frac{1}{1-\theta_2}\frac{1}{1-\theta}\hat{\beta}_i x_t + \frac{1}{1-\theta}z_{it}} MPK_{it}^{-\frac{1}{1-\theta}} di\right)$$

The first expression in braces is equal to

$$\frac{1}{1-\theta}\frac{1}{1-\theta_2}\bar{\hat{\beta}}x_t - \frac{\theta}{1-\theta}\bar{m}pk + \frac{1}{2}\left(\frac{1}{1-\theta}\right)^2\left(\left(\frac{1}{1-\theta_2}\right)^2 x_t^2\sigma_{\hat{\beta}}^2 + \sigma_z^2\right) + \frac{1}{2}\left(\frac{\theta}{1-\theta}\right)^2\sigma_{mpk}^2$$

$$- \frac{\theta}{(1-\theta)^2}\frac{1}{1-\theta_2}\sigma_{mpk,\hat{\beta}_i x_t + z_{it}}$$

and the second to

$$\frac{\theta}{1-\theta}\frac{1}{1-\theta_2}\bar{\hat{\beta}}x_t - \frac{\theta}{1-\theta}\bar{m}pk + \frac{1}{2}\theta\left(\frac{1}{1-\theta}\right)^2\left(\left(\frac{1}{1-\theta_2}\right)^2 x_t^2\sigma_{\hat{\beta}}^2 + \sigma_z^2\right) + \frac{1}{2}\theta\left(\frac{1}{1-\theta}\right)^2\sigma_{mpk}^2$$

$$- \frac{\theta}{(1-\theta)^2}\frac{1}{1-\theta_2}\sigma_{mpk,\hat{\beta}_i x_t + z_{it}}$$

and combining (and using $\sigma_\beta = \frac{1}{1-\theta_2}\sigma_{\hat{\beta}}$) gives

$$\begin{aligned}
a_t &= \bar{\hat{\beta}}x_t + (1-\theta_2)\left(\frac{1}{2}\frac{1}{1-\theta}\left(x_t^2\sigma_\beta^2 + \sigma_z^2\right) - \frac{1}{2}\frac{\theta}{1-\theta}\sigma_{mpk}^2\right) \\
&= a_t^* - \frac{1}{2}(1-\theta_2)\frac{\theta}{1-\theta}\sigma_{mpk}^2 \\
&= a_t^* - \frac{1}{2}\frac{\theta_1(1-\theta_2)}{1-\theta_1-\theta_2}\sigma_{mpk}^2
\end{aligned}$$

C.4 Stock Market Returns

We derive stock market returns in the environment with adjustment costs. This nests the simpler case without them when $\xi = 0$.

Dividends are equal to

$$D_{it+1} = e^{z_{it+1}+\beta_i x_{t+1}}K_{it+1}^\theta - K_{it+2} + (1-\delta)K_{it+1} - \frac{\xi}{2}\left(\frac{K_{it+2}}{K_{it+1}} - 1\right)^2 K_{it+1}$$

and log-linearizing,

$$d_{it+1} = \frac{\Pi}{D}(z_{it+1} + \beta_i x_{t+1}) + \left(\theta\frac{\Pi}{D} + (1-\delta)\frac{K}{D}\right)k_{it+1} - \frac{K}{D}k_{it+2} + \log D - \left(\theta\frac{\Pi}{D} - \delta\frac{K}{D}\right)k$$

where $k = \log K$. Substituting for k_{it+1} and k_{it+2} from Appendix C.2 and rearranging,

$$d_{it+1} = A_{0i} + \tilde{A}_1 z_{it} + A_1 \beta_i x_t + \tilde{A}_2 \varepsilon_{it+1} + A_2 \beta_i \varepsilon_{t+1} + A_3 k_{it}$$

where

$$
\begin{aligned}
A_{0i} &= \log D - \left(\theta \frac{\Pi}{D} - \delta \frac{K}{D} \right)(k - \phi_{0i}) - \frac{K}{D}\phi_{0i}\phi_3 \\
A_1 &= \frac{\Pi}{D}\rho_x + \left(\theta \frac{\Pi}{D} + \frac{K}{D}(1 - \delta - \rho_x - \phi_3) \right)\phi_1 \\
\tilde{A}_1 &= \frac{\Pi}{D}\rho_z + \left(\theta \frac{\Pi}{D} + \frac{K}{D}(1 - \delta - \rho_z - \phi_3) \right)\phi_2 \\
A_2 &= \frac{\Pi}{D} - \frac{K}{D}\phi_1 \\
\tilde{A}_2 &= \frac{\Pi}{D} - \frac{K}{D}\phi_2 \\
A_3 &= \left(\theta \frac{\Pi}{D} + \frac{K}{D}(1 - \delta - \phi_3) \right)\phi_3
\end{aligned}
$$

By definition, returns are equal to

$$R_{it+1} = \frac{D_{it+1} + P_{it+1}}{P_{it}}$$

and log-linearizing,

$$r_{it+1} = \rho p_{it+1} + (1 - \rho) d_{it+1} - p_{it} - \log \rho + (1 - \rho) \log \frac{P}{D}$$

Conjecture the stock price takes the form

$$p_{it} = c_{0i} + c_1 \beta_i x_t + c_2 z_{it} + c_3 k_{it}$$

Then,

$$
\begin{aligned}
r_{it+1} = {} & -\log \rho + (1-\rho)\left(\log \frac{P}{D} + A_{0i} - c_{0i}\right) + \rho c_3 \phi_{0i} \\
& + \left((\rho\rho_z - 1)c_2 + \rho c_3 \phi_2 + (1-\rho)\tilde{A}_1\right) z_{it} \\
& + \left((\rho\rho_x - 1)c_1 + \rho c_3 \phi_1 + (1-\rho)A_1\right)\beta_i x_t \\
& + \left((\rho\phi_3 - 1)c_3 + (1-\rho)A_3\right) k_{it} \\
& + \left(\rho c_2 + (1-\rho)\tilde{A}_2\right)\varepsilon_{it+1} + (\rho c_1 + (1-\rho)A_2)\beta_i \varepsilon_{t+1}
\end{aligned}
$$

and the (log) excess return is the (negative of the) conditional covariance with the SDF:

$$
\log \mathbb{E}_t \left[R^e_{it+1}\right] = (\rho c_1 + (1-\rho)A_2)\beta_i \gamma_t \sigma^2_\varepsilon
$$

To solve for the coefficients, use the Euler equation. First,

$$
\begin{aligned}
r_{it+1} + m_{it+1} = {} & (1-\rho)\left(\log \frac{P}{D} + A_{0i} - c_{0i}\right) + \rho c_3 \phi_{0i} - \frac{1}{2}\gamma_0^2 \sigma^2_\varepsilon \\
& + \left((\rho\rho_z - 1)c_2 + \rho c_3 \phi_2 + (1-\rho)\tilde{A}_1\right) z_{it} \\
& + \left(((\rho\rho_x - 1)c_1 + \rho c_3 \phi_1 + (1-\rho)A_1)\beta_i - \gamma_0 \gamma_1 \sigma^2_\varepsilon\right) x_t \\
& + \left((\rho\phi_3 - 1)c_3 + (1-\rho)A_3\right) k_{it} \\
& - \frac{1}{2}\gamma_1^2 \sigma^2_\varepsilon x_t^2 \\
& + \left(\rho c_2 + (1-\rho)\tilde{A}_2\right)\varepsilon_{it+1} \\
& + \left((\rho c_1 + (1-\rho)A_2)\beta_i - \gamma_0 - \gamma_1 x_t\right)\varepsilon_{t+1}
\end{aligned}
$$

The Euler equation implies

$$
\begin{aligned}
0 = {} & \mathbb{E}_t \left[r_{it+1} + m_{it+1}\right] + \frac{1}{2}\text{var}\left(r_{it+1} + m_{it+1}\right) \\
= {} & (1-\rho)\left(\log \frac{P}{D} + A_{0i} - c_{0i}\right) + \rho c_3 \phi_{0i} + \frac{1}{2}(\rho c_1 + (1-\rho)A_2)^2 \beta_i^2 \sigma^2_\varepsilon - (\rho c_1 + (1-\rho)A_2)\beta_i \gamma_0 \sigma^2_\varepsilon \\
& + \frac{1}{2}\left(\rho c_2 + (1-\rho)\tilde{A}_2\right)^2 \sigma^2_\varepsilon \\
& + \left((\rho\rho_z - 1)c_2 + \rho c_3 \phi_2 + (1-\rho)\tilde{A}_1\right) z_{it} \\
& + \left((\rho\rho_x - 1)c_1 + \rho c_3 \phi_1 + (1-\rho)A_1 - (\rho c_1 + (1-\rho)A_2)\gamma_1 \sigma^2_\varepsilon\right)\beta_i x_t \\
& + \left((\rho\phi_3 - 1)c_3 + (1-\rho)A_3\right) k_{it}
\end{aligned}
$$

and so by undetermined coefficients,

$$
\begin{aligned}
0 &= (1-\rho)\left(\log\frac{P}{D} + A_{0i} - c_{0i}\right) + \rho c_3\phi_{0i} + \frac{1}{2}\left(\rho c_1 + (1-\rho)A_2\right)^2\beta_i^2\sigma_\varepsilon^2 - \left(\rho c_1 + (1-\rho)A_2\right)\beta_i\gamma_0\sigma_\varepsilon^2 \\
&\quad + \frac{1}{2}\left(\rho c_2 + (1-\rho)\tilde{A}_2\right)^2\sigma_{\tilde\varepsilon}^2 \\
&= (\rho\rho_z - 1)c_2 + \rho c_3\phi_2 + (1-\rho)\tilde{A}_1 \\
&= (\rho\rho_x - 1)c_1 + \rho c_3\phi_1 + (1-\rho)A_1 - \left(\rho c_1 + (1-\rho)A_2\right)\gamma_1\sigma_\varepsilon^2 \\
&= (\rho\phi_3 - 1)c_3 + (1-\rho)A_3
\end{aligned}
$$

or

$$
\begin{aligned}
c_3 &= \frac{(1-\rho)A_3}{1-\rho\phi_3} \\
c_2 &= \frac{\rho c_3\phi_2 + (1-\rho)\tilde{A}_1}{1-\rho\rho_z} \\
c_1 &= \frac{\rho c_3\phi_1 + (1-\rho)\left(A_1 - A_2\gamma_1\sigma_\varepsilon^2\right)}{1-\rho\rho_x + \rho\gamma_1\sigma_\varepsilon^2}
\end{aligned}
$$

Substituting for c_1 we can solve for

$$
\log\mathbb{E}_t\left[R_{it+1}^e\right] = \frac{\rho^2 c_3\phi_1 + (1-\rho)\left(\rho A_1 + (1-\rho\rho_x)A_2\right)}{1-\rho\rho_x + \rho\sigma_\varepsilon^2\gamma_1}\beta_i\gamma_t\sigma_\varepsilon^2
$$

Solving for

$$
\begin{aligned}
\rho A_1 + (1-\rho\rho_x)A_2 &= \frac{\frac{1}{\rho} + \delta - 1 - \rho\theta\phi_1\phi_3}{\frac{1}{\rho} + \delta(1-\theta) - 1} \\
\rho^2 c_3\phi_1 &= \theta\frac{\rho^2(1-\rho)\phi_1\phi_3}{1-\rho\phi_3}\frac{\frac{1}{\rho} - \phi_3}{\frac{1}{\rho} + \delta(1-\theta) - 1}
\end{aligned}
$$

substituting into the return equation and simplifying, we obtain

$$
\log\mathbb{E}_t\left[R_{it+1}^e\right] = \psi\beta_i\gamma_t\sigma_\varepsilon^2
$$

where

$$
\psi = \frac{\frac{1}{\rho} + \delta - 1}{\frac{1}{\rho} + \delta(1-\theta) - 1}\frac{1-\rho}{1-\rho\rho_x + \rho\gamma_1\sigma_\varepsilon^2}
$$

which is equation (20) in the text.

The Sharpe ratio is the ratio of expected excess returns to the conditional standard deviation of the return:

$$SR_{it} = \frac{\psi \beta_i \gamma_t \sigma_\varepsilon^2}{\sqrt{\left(\rho c_2 + (1-\rho)\tilde{A}_2\right)^2 \sigma_{\tilde{\varepsilon}}^2 + \psi^2 \beta_i^2 \sigma_\varepsilon^2}}$$

We can solve for

$$\rho c_2 + (1-\rho)\tilde{A}_2 = \frac{\frac{1}{\rho} + \delta - 1}{\frac{1}{\rho} + \delta(1-\theta) - 1}\frac{1-\rho}{1-\rho\rho_z}$$

and substituting and rearranging gives the expression in footnote 34.

For a perfectly diversified portfolio (i.e., the integral over individual returns) idiosyncratic shocks cancel, i.e., $\sigma_{\tilde{\varepsilon}}^2 = 0$ and $SR_{mt} = \gamma_t \sigma_\varepsilon$.

C.5 Autocorrelation of Investment

To derive the autocorrelation of investment, define net investment as $\Delta k_{it+1} = k_{it+1} - k_{it}$. We use the following:

$$
\begin{aligned}
\mathrm{cov}\left(\Delta z_{it}, z_{it}\right) &= \mathrm{cov}\left((\rho_z - 1)z_{it-1} + \varepsilon_{it} . \rho_z z_{it-1} + \varepsilon_{it}\right) \\
&= \rho_z(\rho_z - 1)\sigma_z^2 + \sigma_{\tilde{\varepsilon}}^2 \\
&= \frac{1}{1+\rho_z}\sigma_{\tilde{\varepsilon}}^2 \\
\mathrm{cov}\left(\Delta k_{it}, z_{it}\right) &= \mathrm{cov}\left(\Delta k_{it}, \rho_z z_{it-1} + \varepsilon_{it}\right) \\
&= \rho_z \mathrm{cov}\left(\Delta k_{it}, z_{it-1}\right) \\
&= \rho_z \mathrm{cov}\left(\phi_1 \beta_i \Delta x_{t-1} + \phi_2 \Delta z_{it-1} + \phi_3 \Delta k_{it-1}, z_{it-1}\right) \\
&= \rho_z \left(\mathrm{cov}\left(\phi_2 \Delta z_{it-1}, z_{it-1}\right) + \phi_3 \mathrm{cov}\left(\Delta k_{it-1}, z_{it-1}\right)\right) \\
&= \rho_z \phi_2 \frac{1}{1+\rho_z}\sigma_{\tilde{\varepsilon}}^2 + \rho_z \phi_3 \mathrm{cov}\left(\Delta k_{it-1}, z_{it-1}\right)
\end{aligned}
$$

so that

$$\mathbb{E}\left[\mathrm{cov}\left(\Delta k_{it}, z_{it}\right)\right] = \frac{\rho_z}{1+\rho_z}\frac{\phi_2 \sigma_{\tilde{\varepsilon}}^2}{1-\phi_3\rho_z}$$

Next,

$$
\begin{aligned}
\mathrm{cov}\left(\Delta k_{it+1}, \Delta z_{it+1}\right) &= \mathrm{cov}\left(\phi_1 \beta_i \Delta x_t + \phi_2 \Delta z_{it} + \phi_3 \Delta k_{it} . (\rho_z - 1)z_{it} + \varepsilon_{it+1}\right) \\
&= \phi_2(\rho_z - 1)\mathrm{cov}\left(\Delta z_{it}, z_{it}\right) + \phi_3(\rho_z - 1)\mathrm{cov}\left(\Delta k_{it}, z_{it}\right) \\
&= \phi_2(\rho_z - 1)\frac{1}{1+\rho_z}\sigma_{\tilde{\varepsilon}}^2 + \frac{\rho_z}{1+\rho_z}\frac{\phi_3(\rho_z - 1)\phi_2 \sigma_{\tilde{\varepsilon}}^2}{1-\phi_3\rho_z} \\
&= \frac{\rho_z - 1}{1+\rho_z}\frac{\phi_2 \sigma_{\tilde{\varepsilon}}^2}{1-\phi_3\rho_z}
\end{aligned}
$$

Similar steps give

$$\text{cov}\left(\Delta k_{it+1}, \Delta x_{t+1}\right) = \frac{\rho_x - 1}{1 + \rho_x} \frac{\phi_1 \beta_i \sigma_\varepsilon^2}{1 - \phi_3 \rho_x}$$

Combining these gives the variance of investment:

$$
\begin{aligned}
\sigma_{\Delta k}^2 &= \phi_1^2 \beta_i^2 \text{var}\left(\Delta x_t\right) + \phi_2^2 \text{var}\left(\Delta z_{it}\right) + \phi_3^2 \sigma_{\Delta k}^2 \\
&+ 2\phi_1 \phi_3 \beta_i \text{cov}\left(\Delta x_t, \Delta k_{it}\right) + 2\phi_2 \phi_3 \text{cov}\left(\Delta z_{it}, \Delta k_{it}\right) \\
&= \phi_1^2 \beta_i^2 \frac{2}{1 + \rho_x} \sigma_\varepsilon^2 + \phi_2^2 \frac{2}{1 + \rho_z} \sigma_{\tilde{\varepsilon}}^2 + \phi_3^2 \sigma_{\Delta k}^2 \\
&+ \frac{2\phi_1^2 \phi_3 \beta_i^2 \sigma_\varepsilon^2}{1 - \phi_3 \rho_x} \frac{\rho_x - 1}{1 + \rho_x} + \frac{2\phi_2^2 \phi_3 \sigma_{\tilde{\varepsilon}}^2}{1 - \phi_3 \rho_z} \frac{\rho_z - 1}{1 + \rho_z} \\
&= \phi_3^2 \sigma_{\Delta k}^2 + 2\phi_1^2 \beta_i^2 \frac{\sigma_\varepsilon^2}{1 + \rho_x} \left(1 + \frac{\phi_3 \left(\rho_x - 1\right)}{1 - \phi_3 \rho_x}\right) + 2\phi_2^2 \frac{\sigma_{\tilde{\varepsilon}}^2}{1 + \rho_z} \left(1 + \frac{\phi_3 \left(\rho_z - 1\right)}{1 - \phi_3 \rho_z}\right) \\
&= \frac{2}{1 + \phi_3} \left(\phi_1^2 \beta_i^2 \sigma_\varepsilon^2 \frac{1}{1 + \rho_x} \frac{1}{1 - \phi_3 \rho_x} + \phi_2^2 \sigma_{\tilde{\varepsilon}}^2 \frac{1}{1 + \rho_z} \frac{1}{1 - \phi_3 \rho_z}\right)
\end{aligned}
$$

Next,

$$
\begin{aligned}
\text{cov}\left(\Delta k_{it+1}, \Delta k_{it}\right) &= \text{cov}\left(\phi_1 \beta_i \Delta x_t + \phi_2 \Delta z_{it} + \phi_3 \Delta k_{it}, \Delta k_{it}\right) \\
&= \phi_1 \beta_i \text{cov}\left(\Delta x_t, \Delta k_{it}\right) + \phi_2 \text{cov}\left(\Delta z_{it}, \Delta k_{it}\right) + \phi_3 \sigma_{\Delta k}^2 \\
&= \phi_1^2 \beta_i^2 \sigma_\varepsilon^2 \frac{\rho_x - 1}{1 + \rho_x} \frac{1}{1 - \phi_3 \rho_x} + \phi_2^2 \sigma_{\tilde{\varepsilon}}^2 \frac{\rho_z - 1}{1 + \rho_z} \frac{1}{1 - \phi_3 \rho_z} + \phi_3 \sigma_{\Delta k}^2
\end{aligned}
$$

and the autocorrelation is:

$$\text{corr}\left(\Delta k_{it+1}, \Delta k_{it}\right) = \phi_3 + \frac{1 + \phi_3}{2} \frac{\phi_1^2 \beta_i^2 \sigma_\varepsilon^2 \frac{\rho_x - 1}{1 + \rho_x} \frac{1}{1 - \phi_3 \rho_x} + \phi_2^2 \sigma_{\tilde{\varepsilon}}^2 \frac{\rho_z - 1}{1 + \rho_z} \frac{1}{1 - \phi_3 \rho_z}}{\phi_1^2 \beta_i^2 \sigma_\varepsilon^2 \frac{1}{1 + \rho_x} \frac{1}{1 - \phi_3 \rho_x} + \phi_2^2 \sigma_{\tilde{\varepsilon}}^2 \frac{1}{1 + \rho_z} \frac{1}{1 - \phi_3 \rho_z}} \tag{31}$$

Notice that this approaches

$$\text{corr}\left(\Delta k_{it+1}, \Delta k_{it}\right) = \phi_3 + \left(1 - \phi_3\right) \frac{\rho_x - 1}{2}$$

as ρ_z and ρ_x become close. Further, in the case both shocks follow a random walk, the auto-correlation is simply equal to ϕ_3.

D   Numerical Procedure

Our numerical approach to parameterize the model is as follows. To accurately capture the properties of the time-varying risk premium, we solve for returns numerically using a fourth-

order approximation in Dynare++. For a given set of the parameters γ_0, γ_1, ξ and σ_β^2, we solve the model for a wide grid of beta-types centered around the mean beta. We use an 11 point grid ranging from -3 to 7 (the results are not overly sensitive to the width of the grid). We simulate a time series of excess returns for a large number of firms of each type, which results in a large panel of excess returns. Averaging returns across these firms in each time period yields a series for the market excess return. We can then compute the mean and standard deviation (i.e., Sharpe ratio) of the market return.

Next, we compute the expected return for each beta-type in each time period directly as the conditional expectation $\mathbb{E}_t[R_{it+1}] = \mathbb{E}_t\left[\frac{D_{it+1}+P_{it+1}}{P_{it}}\right]$ and then average over the time periods to obtain the average expected return for firms of each type. We then use these values to calculate the dispersion in expected returns, σ_{Er}^2, interpolating for values of β that are not on the grid. We use a simulated investment series to calculate the autocorrelation of investment.

Finally, we find the set of the four parameters, γ_0, γ_1, σ_β^2 and ξ that make the simulated moments consistent with the empirical ones, i.e., (i) market excess return, (ii) market Sharpe ratio, (iii) cross-sectional dispersion in expected returns and (iv) the autocorrelation of investment. As shown in column (1) of the bottom panel of Table 7, the simulated moments are quite close to their empirical counterparts.

E   Extensions

Our baseline framework in Section 4 features (i) a single source of aggregate risk and (ii) a tight connection between financial market conditions and the "real" side of the economy – indeed, the state of technology determined both the common component of firm-level productivities and the price of risk simultaneously. In this appendix, we generalize that setup to allow for (i) multiple risk factors and (ii) more flexible formulations of the determinants of financial conditions. Although empirically disciplining the additional factors added here may be challenging, we demonstrate that the same insights from the baseline analysis go through.

E.1   Multifactor Model

There are J aggregate risk factors in the economy. Firms have heterogeneous loadings on these factors, so that the profit function (in logs) takes the form

$$\pi_{it} = \beta_i x_t + z_{it} + \theta k_{it} \tag{32}$$

where β_i is a vector of factor loadings of firm i, e.g., the j-th element of β_i is the loading of firm i profits on factor j, and x_t is the vector of factor realizations at time t, i.e.,

$$\beta_i = \begin{bmatrix} \beta_{1i} \\ \beta_{2i} \\ \vdots \\ \beta_{Ji} \end{bmatrix}' \qquad x_t = \begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{Jt} \end{bmatrix}'$$

Each factor, indexed by j, follows an AR(1) process

$$x_{jt+1} = \rho_j x_{jt} + \varepsilon_{jt+1}, \quad \varepsilon_{jt+1} \sim \mathcal{N}\left(0, \sigma_{\varepsilon_j}^2\right) \tag{33}$$

where the innovations are potentially correlated across factors. Denote by Σ_f the covariance matrix of factor innovations, i.e.,

$$\Sigma_f = \begin{bmatrix} \sigma_{\varepsilon_1}^2 & \sigma_{\varepsilon_1,\varepsilon_2} & \cdots & \sigma_{\varepsilon_1,\varepsilon_J} \\ \sigma_{\varepsilon_2,\varepsilon_1} & \sigma_{\varepsilon_2}^2 & \cdots & \sigma_{\varepsilon_2,\varepsilon_J} \\ \vdots & \vdots & & \vdots \\ \sigma_{\varepsilon_J,\varepsilon_1} & \sigma_{\varepsilon_J,\varepsilon_2} & \cdots & \sigma_{\varepsilon_J}^2 \end{bmatrix}$$

The idiosyncratic component of firm productivity follows

$$z_{it+1} = \rho_z z_{it} + \varepsilon_{it+1}, \quad \varepsilon_{it+1} \sim \mathcal{N}\left(0, \sigma_{\tilde{\varepsilon}}^2\right) \tag{34}$$

The stochastic discount factor takes the form

$$m_{t+1} = \log \rho - \gamma \varepsilon_{t+1} - \frac{1}{2}\gamma \Sigma_f \gamma' \tag{35}$$

where γ is a vector of factor exposures, e.g., element γ_j captures the exposure of the SDF to the j-th factor, and ε_{t+1} is the vector of innovations in each factor, i.e.,

$$\gamma = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_J \end{bmatrix}' \qquad \varepsilon_{t+1} = \begin{bmatrix} \varepsilon_{1t+1} \\ \varepsilon_{2t+1} \\ \vdots \\ \varepsilon_{Jt+1} \end{bmatrix}$$

For purposes of illustration, we assume γ is constant through time and there are no adjustment costs, although these assumptions are easily relaxed. Expressions (32), (33), (34) and (35) are

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simple extensions of (10), (8) and (9).

Following a similar derivation as Appendix C.1, we can derive the realized mpk:

$$mpk_{it+1} = \alpha + \varepsilon_{it+1} + \beta_i \varepsilon_{t+1} + \beta_i \Sigma_f \gamma'$$

where β_i and ε_{t+1} denote vectors of factor loadings and shocks. The expected mpk and its cross-sectional dispersion are given by

$$\mathbb{E}_t [mpk_{it+1}] = \alpha + \beta_i \Sigma_f \gamma', \quad \sigma^2_{\mathbb{E}_t[mpk]} = \gamma \Sigma'_f \Sigma_\beta \Sigma_f \gamma'$$

where Σ_β is the covariance matrix of factor loadings across firms, i.e.,

$$\Sigma_\beta = \begin{bmatrix} \sigma^2_{\beta_1} & \sigma_{\beta_1,\beta_2} & \cdots & \sigma_{\beta_1,\beta_J} \\ \sigma_{\beta_2,\beta_1} & \sigma^2_{\beta_2} & \cdots & \sigma_{\beta_2,\beta_J} \\ \vdots & \vdots & & \vdots \\ \sigma_{\beta_J,\beta_1} & \sigma_{\beta_J,\beta_2} & \cdots & \sigma^2_{\beta_J} \end{bmatrix}$$

This is the natural analog of expression (15): (i) expected mpk is determined by the firm's exposure to (all) the aggregate risk factors in the economy and the risk prices of those factors, and (ii) mpk dispersion is a function of the dispersion in those exposures across firms as captured by Σ_β.

Similar steps as Appendix C.4 gives the following (approximate) expression for expected excess stock returns and the cross-sectional dispersion in expected returns:

$$Er^e_{it+1} = \beta_i \psi \Sigma_f \gamma', \quad \sigma^2_{Er^e_t} = \gamma \Sigma'_f \psi' \Sigma_\beta \psi \Sigma_f \gamma'$$

where ψ is a diagonal matrix with

$$\psi_{jj} = \frac{\frac{1}{\rho} + \delta - 1}{\frac{1}{\rho} + (1-\theta)\delta - 1} \frac{1-\rho}{1-\rho\rho_j}$$

where ρ_j denotes the persistence of factor j. These are the analogs of expressions (20) and (21) – expected returns depend on factor exposures and the risk prices of those factors. Expected return dispersion depends on the dispersion in those exposures, here captured by Σ_β.

Thus, the same insights from the single factor model go through – dispersion in $Empk$ and expected returns are both determined by variation in exposures to the set of aggregate factors and hence, there is a tight relationship between the two. To quantify the impact of these factors on mpk dispersion, however, we would need to know all the primitives governing the dynamics

of the factors, e.g., the vector of persistences ρ and the covariance matrix Σ_f, and exposures, i.e., the exposures of the SDF, γ, and the vectors of firm loadings, Σ_β. This would likely entail taking a stand on the nature of each factor, computing their properties from the data and calibrating/estimating the γ vector and the covariance matrix of firm exposures, Σ_β.

E.2 Financial Shocks

Our baseline model tightly linked financial conditions, for example, the price of risk, to macroeconomic conditions, i.e., the state of aggregate technology. However, financial conditions may not co-move one-for-one with the "real" business cycle. Here, we extend the setup to include pure financial shocks. The stochastic discount factor takes the form

$$
\begin{aligned}
m_{t+1} &= \log \rho - \gamma_t \varepsilon_{t+1} - \frac{1}{2}\gamma_t^2 \sigma_\varepsilon^2 \\
\gamma_t &= \gamma_0 + \gamma_f f_t ,
\end{aligned}
\tag{36}
$$

where

$$
f_{t+1} = \rho_f f_t + \varepsilon_f, \quad \varepsilon_f \sim \mathcal{N}\left(0, \sigma_{\varepsilon_f}^2\right) .
$$

In this formulation, f_t denotes the time-varying state of financial conditions, which is now disconnected from the state of aggregate technology. These financial factors may be correlated with real conditions, x_t, but need not be perfectly so. Thus, there is scope for changes in financial conditions, independent of those in real conditions, to affect the price of risk and through this channel, the allocation of capital.[59] Note the difference between this setup and the one in Section E.1 – here, the financial factor, f_t, does not directly enter the profit function of the firm, it only affects the price of risk. Thus, it is a shock purely to financial market conditions. In contrast, the factors considered in Section E.1 directly affected firm profitability.

Keeping the remainder of the environment the same as Section 4, we can derive exactly the same expressions for expected mpk and its cross-sectional variance, i.e.,

$$
\mathbb{E}_t\left[mpk_{it+1}\right] = \alpha + \beta_i \gamma_t \sigma_\varepsilon^2, \quad \sigma_{\mathbb{E}_t[mpk_{it+1}]}^2 = \sigma_\beta^2 \left(\gamma_t \sigma_\varepsilon^2\right)^2 ,
$$

where now γ_t is a function of financial market conditions. When credit market conditions tighten (i.e., when f_t is small/negative since $\gamma_f < 0$), γ_t is high and mpk dispersion will rise.

Just as in Section 4, the conditional expectation of one-period ahead TFP is given by

$$
\mathbb{E}_t\left[a_{t+1}\right] = \mathbb{E}_t\left[a_{t+1}^*\right] - \frac{1}{2}\frac{\theta_1\left(1 - \theta_2\right)}{1 - \theta_1 + \theta_2}\sigma_\beta^2 \left(\gamma_t \sigma_\varepsilon^2\right)^2
\tag{37}
$$

---

[59]Our baseline model is the nested case where $\gamma_f = \gamma_1$ and f_t and x_t are perfectly correlated.

which illustrates the effects of a deterioration in financial conditions on macroeconomic performance – when credit market conditions tighten and risk premia rise (i.e., f_t falls), the resulting increase in mpk dispersion leads to a fall in aggregate TFP.

Finally, the average long-run level of $Empk$ dispersion and aggregate TFP are given by

$$\mathbb{E}\left[\sigma^2_{Empk_t}\right] = \sigma^2_\beta \left(\gamma^2_0 + \gamma^2_f \sigma^2_f\right)\left(\sigma^2_{\varepsilon_f}\right)^2, \quad \bar{a} = a^* - \frac{1}{2}\frac{\theta_1\left(1-\theta_2\right)}{1-\theta_1-\theta_2}\sigma^2_\beta\left(\gamma^2_0 + \gamma^2_f \sigma^2_f\right)\left(\sigma^2_{\varepsilon_f}\right)^2,$$

where $\sigma^2_f = \frac{\sigma^2_{\varepsilon_f}}{1-\rho^2_f}$. The expressions reveal a tight connection between financial conditions and long-run performance of the economy – higher financial volatility ($\sigma^2_{\varepsilon_f}$), even independent of the state of the macroeconomy, induces greater persistent MPK dispersion and depresses the average level of achieved productivity.

F   Other Distortions

With other distortions, the derivations are similar to those in Appendix C.1. The Euler equation is given by

$$\begin{aligned}
1 &= \mathbb{E}_t\left[M_{t+1}\left(\theta e^{\tau_{it+1}+z_{it+1}+\beta_i x_{t+1}}GK^{\theta-1}_{it+1} + 1 - \delta\right)\right]\\
&= (1-\delta)\mathbb{E}_t\left[M_{t+1}\right] + \theta GK^{\theta-1}_{it+1}\mathbb{E}_t\left[e^{m_{t+1}+\tau_{it+1}+z_{it+1}+\beta_i x_{t+1}}\right]
\end{aligned}$$

Idiosyncratic distortions.   Substituting for m_{t+1} and τ_{it+1} and rearranging,

$$\begin{aligned}
\mathbb{E}_t\left[e^{m_{t+1}+\tau_{it+1}+z_{it+1}+\beta_i x_{t+1}}\right] &= \mathbb{E}_t\left[e^{\log\rho - \gamma_t \varepsilon_{t+1} - \frac{1}{2}\gamma^2_t\sigma^2_\varepsilon - \nu_1 z_{it+1} - \eta_{it+1} + z_{it+1} + \beta_i x_{t+1}}\right]\\
&= \mathbb{E}_t\left[e^{\log\rho + (1-\nu)\rho_z z_{it} + (1-\nu_1)\varepsilon_{it+1} + \beta_i \rho_x x_t + (\beta_i - \gamma_t)\varepsilon_{t+1} - \frac{1}{2}\gamma^2_t\sigma^2_\varepsilon - \eta_{it+1}}\right]\\
&= e^{\log\rho + (1-\nu_1)\rho_z z_{it} + \beta_i \rho_x x_t + \frac{1}{2}(1-\nu_1)^2\sigma^2_{\tilde\varepsilon} + \frac{1}{2}\beta^2_i\sigma^2_\varepsilon - \beta_i\gamma_t\sigma^2_\varepsilon - \eta_{it+1}}
\end{aligned}$$

so that

$$\theta GK^{\theta-1}_{it+1} = \frac{1-(1-\delta)\rho}{e^{\log\rho + (1-\nu_1)\rho_z z_{it} + \beta_i \rho_x x_t + \frac{1}{2}(1-\nu_1)^2\sigma^2_{\tilde\varepsilon} + \frac{1}{2}\beta^2_i\sigma^2_\varepsilon - \beta_i\gamma_t\sigma^2_\varepsilon - \eta_{it+1}}}$$

and rearranging and taking logs,

$$k_{it+1} = \frac{1}{1-\theta}\left(\tilde\alpha + \frac{1}{2}(1-\nu_1)^2\sigma^2_{\tilde\varepsilon} + \frac{1}{2}\beta^2_i\sigma^2_\varepsilon + (1-\nu_1)\rho_z z_{it} + \beta_i \rho_x x_t - \beta_i\gamma_t\sigma^2_\varepsilon - \eta_{it+1}\right)$$

where $\tilde\alpha$ and α are as defined in Appendix C.1.

The realized *mpk* is given by (ignoring the variance terms)

$$
\begin{aligned}
mpk_{it+1} &= \log\theta + \pi_{it+1} - k_{it+1} \\
&= \log\theta + \log G + z_{it+1} + \beta_i x_{t+1} - (1-\theta)\, k_{it+1} \\
&= \log\theta + \log G + z_{it+1} + \beta_i x_{t+1} - \tilde{\alpha} - (1-\nu_1)\,\rho_z z_{it} - \beta_i \rho_x x_t + \beta_i \gamma_t \sigma_\varepsilon^2 + \eta_{it+1} \\
&= \alpha + \varepsilon_{it+1} + \beta_i \varepsilon_{t+1} + \nu_1 \rho_z z_{it} + \beta_i \gamma_t \sigma_\varepsilon^2 + \eta_{it+1}
\end{aligned}
$$

The conditional expected *mpk* is

$$
\mathbb{E}_t\left[mpk_{it+1}\right] = \alpha + \nu_1 \rho_z z_{it} + \beta_i \gamma_t \sigma_\varepsilon^2 + \eta_{it+1}
$$

and the cross-sectional variance is

$$
\sigma^2_{\mathbb{E}_t[mpk_{it+1}]} = (\nu_1 \rho_z)^2\, \sigma_z^2 + \sigma_\eta^2 + \left(\gamma_t \sigma_\varepsilon^2\right)^2 \sigma_\beta^2 \tag{38}
$$

Deriving stock returns follows closely the steps in Appendix C.4. Dividends are equal to

$$
D_{it+1} = e^{\tau_{it+1} + z_{it+1} + \beta_i x_{t+1}} K_{it+1}^\theta - K_{it+2} + (1-\delta) K_{it+1} - \frac{\xi}{2}\left(\frac{K_{it+2}}{K_{it+1}} - 1\right)^2 K_{it+1}
$$

and log-linearizing,

$$
d_{it+1} = \frac{\Pi}{D}\left(\tau_{it+1} + z_{it+1} + \beta_i x_{t+1}\right) + \left(\theta\frac{\Pi}{D} + (1-\delta)\frac{K}{D}\right) k_{it+1} - \frac{K}{D} k_{it+2} + \log D - \left(\theta\frac{\Pi}{D} - \delta\frac{K}{D}\right) k
$$

where $k = \log K$.

Substituting for k_{it+1} and k_{it+2} from above,

$$
d_{it+1} = A_0 + \tilde{A}_1 z_{it} + A_1 \beta_i x_t + \tilde{A}_2 \varepsilon_{it+1} + A_2 \beta_i \varepsilon_{t+1} + A_3 \eta_{it+1} + A_4 \eta_{it+2}
$$

where

$$A_0 = \log D - \left(\theta \frac{\Pi}{D} - \delta \frac{K}{D} \right) \left(k - \frac{\tilde{\alpha}}{1 - \theta} \right)$$

$$A_1 = \frac{1}{1 - \theta} \left(\frac{\Pi}{D} + (1 - \delta - \rho_x) \frac{K}{D} \right) \rho_x - \frac{1}{1 - \theta} \left(\theta \frac{\Pi}{D} + (1 - \delta - \rho_x) \frac{K}{D} \right) \gamma_1 \sigma_\varepsilon^2$$

$$\tilde{A}_1 = \frac{1 - \nu_1}{1 - \theta} \left(\frac{\Pi}{D} + (1 - \delta - \rho_z) \frac{K}{D} \right) \rho_z$$

$$A_2 = \frac{\Pi}{D} - \frac{1}{1 - \theta} \frac{K}{D} \rho_x + \frac{1}{1 - \theta} \frac{K}{D} \gamma_1 \sigma_\varepsilon^2$$

$$\tilde{A}_2 = \left(\frac{\Pi}{D} - \frac{1}{1 - \theta} \frac{K}{D} \right) (1 - \nu_1) \rho_z$$

$$A_3 = -\frac{1}{1 - \theta} \left(\theta \frac{\Pi}{D} + (1 - \delta) \frac{K}{D} \right)$$

$$A_4 = \frac{1}{1 - \theta} \frac{K}{D}$$

Using the log-linearized return equation,

$$r_{it+1} = \rho p_{it+1} + (1 - \rho) d_{it+1} - p_{it} - \log \rho + (1 - \rho) \log \frac{P}{D}$$

and conjecturing the stock price takes the form

$$p_{it} = c_{0i} + c_1 \beta_i x_t + c_2 z_{it} + c_3 \eta_{it+1}$$

gives

$$
\begin{aligned}
r_{it+1} = {} & - \log \rho + (1 - \rho) \left(\log \frac{P}{D} + A_0 - c_0 \right) \\
& + \left((\rho \rho_z - 1) c_2 + (1 - \rho) \tilde{A}_1 \right) z_{it} \\
& + \left((\rho \rho_x - 1) c_1 + (1 - \rho) A_1 \right) \beta_i x_t \\
& + \left(\rho c_2 + (1 - \rho) \tilde{A}_2 \right) \varepsilon_{it+1} + (\rho c_1 + (1 - \rho) A_2) \beta_i \varepsilon_{t+1} \\
& + (\rho c_3 + (1 - \rho) A_4) \eta_{it+2} + ((1 - \rho) A_3 - c_3) \eta_{it+1}
\end{aligned}
$$

The (log) excess return is the (negative of the) conditional covariance with the SDF:

$$\log \mathbb{E}_t \left[R_{it+1}^e \right] = (\rho c_1 + (1 - \rho) A_2) \beta_i \gamma_t \sigma_\varepsilon^2$$

A_2 is independent of ν_1 and η. Following the same steps as in Appendix C.4, it is easily verified that c_1 is independent of these terms as well. Thus, expected returns are independent

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of distortions.

Aggregate distortions. Consider the first formulation, i.e.,

$$\tau_{it+1} = -\nu_1 z_{it+1} - \nu_2 x_{t+1} - \eta_{it+1}$$

Similar steps as above give expression (38). Dispersion in expected stock market returns are similarly unaffected.

Next, consider the second formulation:

$$\tau_{it+1} = -\nu_1 z_{it+1} - \nu_3 \beta_i x_{t+1} - \eta_{it+1}$$

In this case, similar steps as above give the conditional expected mpk as

$$\mathbb{E}_t [mpk_{it+1}] = \alpha + \nu_1 \rho_z z_{it} + \nu_3 \beta_i \rho_x x_t + (1 - \nu_3) \beta_i \gamma_t \sigma_\varepsilon^2 + \eta_{it+1}$$

and expected excess stock market returns as

$$\log \mathbb{E}_t \left[R_{it+1}^e \right] = (1 - \nu_3) \psi \beta_i \gamma_t \sigma_\varepsilon^2$$

where ψ is as defined in expression (20). In other words, the risk-premium effect on expected mpk, as well as expected returns, are both scaled by a factor $1 - \nu_3$.

The mean level of expected mpk and return dispersion are, respectively,

$$
\begin{aligned}
\mathbb{E} \left[\sigma_{\mathbb{E}_t[mpk_{it+1}]}^2 \right] &= \sigma_\eta^2 + (\nu_1 \rho_z)^2 \sigma_z^2 + (\nu_3 \rho_x)^2 \sigma_x^2 \sigma_\beta^2 \\
&\quad + \left((1 - \nu_3) \sigma_\varepsilon^2 \right)^2 \left(\gamma_0^2 + \gamma_1^2 \sigma_x^2 \right) \sigma_\beta^2 + 2 \nu_3 (1 - \nu_3) \rho_x \sigma_x^2 \gamma_1 \sigma_\varepsilon^2 \sigma_\beta^2 \\
\mathbb{E} \left[\sigma_{\log \mathbb{E}_t \left[R_{it+1}^e \right]}^2 \right] &= \left((1 - \nu_3) \psi \sigma_\varepsilon^2 \right)^2 \left(\gamma_0^2 + \gamma_1^2 \sigma_x^2 \right) \sigma_\beta^2
\end{aligned}
$$

The last two terms of the first equation capture the mpk effects of risk premia. The last term there is new and does not have a counterpart in the second equation – in other words, using dispersion in expected returns would give the second to last term, as usual, but not the last. If $\nu_3 < 0$, it is straightforward to verify that that term is positive (recall that γ_1 is negative). Then, we may be understating risk premium effects. If $\nu_3 > 0$, the last terms is negative and we may be overstating them.

In this case, our empirical results suggest a tight upper bound on the extent of the potential bias – specifically, the fact that $Empk$ is countercyclical from prediction (2). To see this,

consider the following expression for $Empk$:

$$
\begin{aligned}
\mathbb{E}_t\left[mpk_{it+1}\right] &= \alpha + \nu_1\rho_z z_{it} + \nu_3\beta_i\rho_x x_t + (1-\nu_3)\beta_i\gamma_t\sigma_\varepsilon^2 + \eta_{it+1} \\
&= \alpha + \nu_1\rho_z z_{it} + \left(\nu_3\rho_x + (1-\nu_3)\gamma_1\sigma_\varepsilon^2\right)\beta_i x_t + (1-\nu_3)\beta_i\gamma_0\sigma_\varepsilon^2 + \eta_{it+1}\ .
\end{aligned}
$$

The fact that $Empk$ is countercyclical implies that the term in parentheses multiplying x_t should be negative, which puts the following bound on ν_3:

$$
\frac{\nu_3}{1-\nu_3} < -\frac{\gamma_1\sigma_\varepsilon^2}{\rho_x}
$$

Intuitively, a positive value of ν_3 implies that the distortion is procyclical and so adds a procyclical element to $Empk$. That $Empk$ is actually countercyclical then puts a sharp bound on how large a positive value ν_3 can take. Using the parameter estimates from Section 5.1, the maximum value of ν_3 is about 0.08. Using this value, along with the other parameters, to calculate the last term in the variance equation gives the maximum upward bias in our estimates of risk-based dispersion in $Empk$, which turns out to be negligible.

G Robustness – Productivity Betas

In this appendix, we investigate the potential effects of (i) mis-measurement of firm-level capital and (ii) unobserved heterogeneity in θ on our estimates of productivity betas in Section 5.4. First, to see the effects of mis-measured capital or measurement error, assume that the measured capital stock is $\hat{k}_{it} = k_{it} + e_{it}$, where k_{it} is true capital and e_{it} the mis-measurement. Measured firm-level productivity growth is then equal to $\Delta z_{it} + \beta_i\Delta x_t - \theta\Delta e_{it}$. Regressing this on measures of aggregate productivity, i.e., Δx_t, it is straightforward to see that the estimated β's would be unaffected so long as changes in mis-measurement at the firm-level (Δe_{it}) are uncorrelated with the business cycle, which may be a reasonable conjecture. Put another way, mis-measured capital in this analysis leads to measurement errors in the dependent variable, which, under relatively mild conditions, are innocuous.[60]

How about unobserved heterogeneity in θ? It turns out this will have small effects as well. To see this, let θ_i denote the true firm-specific parameter and θ our assumed common value. Measured firm-level productivity growth is then equal to $\Delta z_{it} + \beta_i\Delta x - (\theta - \theta_i)\Delta k_{it}$ and regressing this on aggregate productivity growth gives $\beta_i - \frac{(\theta - \theta_i)\mathrm{cov}(\Delta k_{it}, \Delta x_t)}{\mathrm{var}(\Delta x_t)}$, where $\beta_i =$

---

[60]Moreover, a non-zero correlation between Δe_{it} and Δx_t is not itself sufficient to bias the estimates of beta dispersion. In the case of a non-zero correlation, the regression yields $\beta_i - \theta\frac{\mathrm{cov}(\Delta e_{it}, \Delta x_t)}{\mathrm{var}(\Delta x_t)}$. Thus, if the stochastic process on e_{it} is common across firms, this will add a constant bias to the beta estimates, but will not affect our estimates of dispersion.

$\frac{\hat{\beta}_i - \theta_{2i}\omega}{1 - \theta_{2i}}$ is the effective true β (see Section 6 and Appendix H for a further discussion of this expression). The second term represents the potential bias, which depends on the covariance between investment and changes in aggregate productivity. How large is this covariance? As one example, consider the case with no adjustment costs and a constant price of risk. We can use the firm's optimality condition to analytically characterize the covariance, which gives the bias term to be $-\frac{(\theta - \theta_i)\text{cov}(\Delta k_{it}, \Delta x_t)}{\text{var}(\Delta x_t)} = \frac{1}{2}\frac{\theta - \theta_i}{1 - \theta_i}\beta_i\rho_x(1 - \rho_x)$. This term turns out to be negligible. Intuitively, because of time-to-build, investment in period $t + 1$ capital is chosen in period t, before the innovation in productivity is realized. Because of this, the covariance between changes in capital and contemporaneous productivity is quite small and is only non-zero due to mean reversion in the AR(1) process (indeed, if productivity follows a random walk or is iid, i.e., $\rho_x = 1$ or $\rho_x = 0$, the bias term is zero).[61] To verify this result quantitatively, we have simulated data under the extreme case where heterogeneity in θ_i is the only source of beta dispersion (we use the distribution of θ described in Appendix H). As described there, the true standard deviation of beta is 1.35; the biased estimate is 1.38. Although analytic expressions are not available in the full model with adjustment costs and time-varying risk, we have simulated this case as well – the biased estimate remains extremely close to the truth, 1.39. In sum, because the productivity betas are estimated off of covariances, they are extremely robust to concerns of both measurement of capital and unobserved parameter heterogeneity.

H   The Sources of Betas

Heterogeneous technologies.   With heterogeneity in input elasticities, the production function for firm i is

$$Y_{it} = X_t^{\hat{\beta}_i}\hat{Z}_{it}K_{it}^{\theta_{1i}}N_{it}^{\theta_{2i}} \tag{39}$$

In this case, we must make a distinction between mpk and the average product of capital, $apk = y_{it} - k_{it}$, which is the object we measure in the data. With common parameters, these are proportional. With parameter heterogeneity, they are not. Following similar steps to Section 4.1, we can derive

$$apk_{it+1} = -\log\theta_{1i} + \varepsilon_{it+1} + \beta_i\varepsilon_{t+1} + \beta_i\gamma_t\sigma_\varepsilon^2 + \text{constant} \tag{40}$$

where

$$\beta_i \equiv \frac{\hat{\beta}_i - \theta_{2i}\omega}{1 - \theta_{2i}}$$

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[61]Industry-level heterogeneity is a special case where θ varies across industries but not across firms within an industry.

In other words, an expression analogous to (13) holds, with two differences: first, variation in capital elasticities, θ_{1i}, will directly lead to *apk* dispersion through the first term in (40). Second, the effective beta is now a combination of the direct sensitivity to the aggregate shock, $\hat{\beta}_i$, and the firm-specific labor elasticity, θ_{2i}. Variation in θ_{2i} leads firms to have different exposures to changes in labor market conditions, captured through the cyclicality of wages, ω. To gain intuition, consider the extreme case where all heterogeneity in business cycle exposure comes through θ_{2i}, i.e., $\hat{\beta}_i = 1 \ \forall \ i$. Then, $\beta_i = \frac{1-\theta_{2i}\omega}{1-\theta_{2i}}$. It is straightforward to show that β_i is increasing in θ_{2i} as long as $\omega < 1$, i.e., holding all else equal, labor intensive firms are more exposed to cyclical movements in wages, which in and of itself leads to a higher risk premium.[62] Given this simple reinterpretation of beta, a version of the analysis in Section 4 continues to hold. In particular, we can derive an expression for expected stock markets returns that is analogous to (20), but which now also reflects the variation in θ_{2i} – in other words, this type of heterogeneity should be picked up by our empirical measure of variation in risk premia.

How much of the observed beta dispersion can be attributed to variation in production function parameters? Although precisely pinning down its contribution is challenging, we can reach one (likely over-) estimate as follows. First, under the (admittedly strong) assumption that all cross-firm variation in labor's share of income comes from heterogeneity in θ_{2i}, we have $\frac{W_t N_{it}}{Y_{it}} = \theta_{2i}$. This is likely to be an upper bound, since there are many other reasons that labor's share may differ across firms (e.g., labor market frictions or distortions). Donangelo et al. (2018) (Table XII, Panel C) report a cross-sectional standard deviation of labor's share among Compustat firms of 0.186. Using this as an estimate of the dispersion in θ_{2i}, we can calculate the implied beta dispersion. Specifically, we assume that θ_{2i} is normally distributed and discretize the distribution on a seven point grid following the method suggested in Kennan (2006). This yields a range of values for θ_{2i} from 0.31 to 0.84 with standard deviation 0.183. Next, we compute the implied betas as $\beta_i = \frac{1-\theta_{2i}\omega}{1-\theta_{2i}}$. The standard deviation of the betas is 1.35, which represents about 12% of the overall standard deviation of betas in Section 5.[63]

Heterogeneous markups. As is well known in the literature, the production function in expression (7) with decreasing returns to scale is isomorphic to a revenue function that arises with monopolistically competitive firms that produce differentiated products and face constant elasticity demand functions. Specifically, assume that demand and production for firm i take

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[62]Donangelo et al. (2018) explore a related mechanism and provide empirical support for the connection between "labor leverage" and risk premia. They also find that a necessary condition for this relationship to hold is that wages are less than perfectly procyclical, i.e., ω must be less than one.

[63]David and Venkateswaran (2017) investigate technology heterogeneity in detail in a related framework and provide a sharper upper bound on the extent of this heterogeneity. We have also used their estimate for Compustat firms and found similar, though somewhat smaller, results.

the forms

$$Q_{it} = P_{it}^{-\mu_i}, \quad Y_{it} = X_t^{\tilde{\beta}_i} \tilde{Z}_{it} K_{it}^{\tilde{\theta}_1} N_{it}^{\tilde{\theta}_2}$$

where μ_i denotes the (potentially firm-specific) elasticity of demand and $\tilde{\theta}_j$, $j = 1, 2$ the technological parameters in the production function, which for this section are assumed to be common across firms. It is straightforward to derive the following expression for firm revenues:

$$P_{it} Y_{it} = X_t^{\hat{\beta}_i} \hat{Z}_{it} K_{it}^{\theta_{1i}} N_{it}^{\theta_{2i}}$$

where $\hat{\beta}_i = \left(1 - \frac{1}{\mu_i}\right) \tilde{\beta}_i$, $\hat{Z}_{it} = \tilde{Z}_{it}^{1 - \frac{1}{\mu_i}}$ and $\theta_{ji} = \left(1 - \frac{1}{\mu_i}\right) \tilde{\theta}_j$, $j = 1, 2$. With these reinterpretations of parameters, this is equivalent to (39) (there, the common price of output is equal to one). Note that for the case of a common demand elasticity, i.e., $\mu_i = \mu$, the analysis from Section 4 goes through exactly. With heterogeneity in demand elasticities, the analysis takes the same form as with technology heterogeneity – variation in technology and markups show up in the same way. Thus, markup dispersion across firms is an additional candidate for heterogeneous exposures and, indeed, should be picked up in our measures of firm-level risk premia. All else equal, firms facing a high demand elasticity (so setting a low markup, which is equal to $\frac{\mu_i}{\mu_i - 1}$) respond more strongly to shocks and so show greater sensitivity to them.

Even with no additional heterogeneity in $\tilde{\beta}_i$, the firm's beta in the revenue function is given by $\hat{\beta}_i = 1 - \frac{1}{\mu_i} = \frac{1}{markup_i}$, i.e., is the inverse of the markup. How much of the measured beta dispersion can variation in markups explain? Recent estimates of the within-industry standard deviation of (log) markups among Compustat firms yield values of about 0.20 (e.g., David and Venkateswaran (2017)).[64] Following a similar approach as in our analysis of technology heterogeneity, we can compute the resulting dispersion in betas. Specifically, we discretize the distribution of log markups on a five point grid. The lowest value on the grid implies a markup less than one, which we set to 1.01. We choose the standard deviation of the distribution so that the standard deviation of the truncated distribution is 0.20. This yields a range of markups from 1.01 to 1.63. After optimizing over labor, the implied beta for firm i is given by $\beta_i = \frac{\hat{\beta}_i - \theta_{2i}\omega}{1 - \theta_{2i}} = \frac{1 - \tilde{\theta}_2\omega}{markup_i - \tilde{\theta}_2}$. We set $\tilde{\theta}_2$ to a standard value of 0.67 and compute the standard deviation of these betas, which is 0.71. This accounts for about 6% of the overall standard deviation calculated in Section 5.

Other parameter heterogeneity. We have also examined the potential effects of two other forms of parameter heterogeneity – in the depreciation rate, δ, and the properties of idiosyncratic

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[64]The statistics reported in Edmond et al. (2018) imply a roughly similar figure. Haltiwanger et al. (2018) find the same value using a different empirical method (namely, estimating a variable elasticity of substitution demand system using detailed data on prices and quantities) on a sample drawn from the Census of Manufactures.

shocks, i.e., their persistence and volatility, ρ_z and $\sigma_{\tilde{\varepsilon}}^2$. To a first-order, the latter two parameters do not enter our estimates of beta dispersion/risk premia anywhere – idiosyncratic shocks, while extremely important in determining firm dynamics, do not affect covariances and so do not lead to risk premia. Expression (20) shows that δ does play a role in determining expected stock returns (through the denominator of ψ, which, with heterogeneity in δ will be firm-specific), but a numerical simulation suggests these effects are small. For example, allowing δ to range from 0.04 to 0.16 (so half and double the baseline value) generates a spread in expected returns of 1.6%, which is modest relative to the extent of expected return dispersion in the data. For example, Table 9 in Appendix A.3 shows that interquartile range of expected returns is almost 12%. Halving/doubling ρ_z and $\sigma_{\tilde{\varepsilon}}^2$ also leads to only limited spreads in expected returns (1.3% and 2.3%, respectively). These results suggest that unobserved heterogeneity in these parameters seems unlikely to account for the substantial dispersion in risk premia observed in the data. Moreover, note that our calculation of productivity betas in Section 5.4 is independent of these parameters, further emphasizing that the majority of the empirical beta dispersion is unlikely to stem from these parameters.[65]

Heterogeneous demand sensitivities. To construct the sample for Figure 1 we first extracted the set of all firms in SIC 5812 for which we have sufficient quarterly observations to compute our measures of risk exposure (20 consecutive quarters are required). Next we obtained data on average check per person. These data are primarily from surveys performed by Citi Research and Morgan Stanley, downloaded from `https://finance.yahoo.com/news/much-costs-eat-every-major-201809513.html`, dated September 2015. Of the firms in the Compustat sample, this gave us pricing data for 8 firms: McDonalds (MCD), Wendy's (WEN), Sonic (SON), Chipotle (CHP), Cheesecake Factory (CHE), Texas Roadhouse (TEX), BJ's Restaurants (BJR) and Red Robin (ROB). We supplemented these data with figures reported in company 10-K filings with the SEC for the year 2014 for Jack in the Box (JCK), Panera Bread (PAN), Carrol's Restaurant Group (the largest Burger King franchisee; BKG), Chili's (CHL), Cracker Barrel (CRA), Bob Evans (BOB), Ruth's Chris Steakhouse (RUT), Denny's (DEN), Famous Dave's (FAM), Kona Grill (KON), Granite City (GRA) and Darden (DAR). Data on Granite City are from its 2013 10-K filing, where we calculated the average of the

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[65]We have also explored the effects of adjustment costs alone by simulating a panel of firms with a common beta and computing the mean of period-by-period expected return dispersion. We find that adjustment costs on their own lead to very little dispersion in expected returns (average standard deviation of about 0.015 compared to 0.127 in the data), suggesting that it is unlikely that our estimates of beta are reflecting the effects of these costs. We have also verified that this result goes through for larger levels of these costs (e.g., $\xi = 3$, compared to 0.04 in the baseline). Note that this is in line with our approximate expression for expected returns in equation (20): that expression show that to a first-order, expected returns are completely independent of adjustment costs.

reported range across markets. Darden owns Eddie V's, Capital Grille, Seasons's 52, Bahama Breeze, Olive Garden, Longhorn Steakhouse, Fleming's, Bonefish Grill, Carraba's and Outback Steakhouse. It reports an average check for each of these chains separately, which we combined into a single value using a sales-weighted average. The largest among this group is Olive Garden. We excluded chains that were confined to a very limited geographic area and those for which we could not obtain average check data. In total, our sample consists of 20 firms. We computed average betas, expected returns and MPK for these firms over the period 2010-2015.

Table 10 presents the full set of correlations across all variables – average check per person, CAPM, demand and Fama-French betas, expected stock returns and MPK. The table shows strong positive correlations between average check and the various beta measures, as well as between average check and returns and MPK. Further, the positive correlations between beta, expected returns and MPK show that high beta and high expected return firms tend to have MPK.

Table 10: Correlations – SIC 5812, Eating Places

	Ln(avg. check)	CAPM Beta	Demand Beta	FF Beta	Expected Return	Ln(MPK)
Ln(avg. check)	1.00					
CAPM Beta	0.47	1.00				
Demand Beta	0.64	0.41	1.00			
FF Beta	0.61	0.85	0.47	1.00		
Expected Return	0.63	0.42	0.37	0.57	1.00	
Ln(MPK)	0.65	0.65	0.63	0.77	0.64	1.00

I Further Empirical Results

I.1 Additional Portfolio Sorts

This appendix reports additional portfolio sorts and summary statistics by portfolio.

Portfolio summary statistics.   Table 11 displays summary statistics of firm characteristics across the industry-adjusted MPK-sorted portfolios.[66] A few observations are in order: while size and book-to-market seem to be correlated with firm MPK, the sorting is not monotonic. There are not large differences in the leverage of high and low MPK firms. One possible concern is that our measure of capital omits intangible capital, and that firms that seem to have high MPK (low capital capital utilization) are using intangible capital instead of physical capital.

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[66]The table displays median firm characteristics, but the means yield qualitatively similar patterns.

The table shows that this is unlikely to be the case – firms with low MPK, who use capital more intensively, also use intangible capital more intensively, as shown by their relatively high research and development (R&D) expenditures (relative to sales) and also their relatively high sales, general, and administrative (SG&A) expenses (relative to sales), two commonly used measures of investment in intangible capital.

Table 11: Firm Characteristics Across MPK-Sorted Portfolios

Portfolio	Low	2	3	4	High	Pooled
mpk	0.588	1.254	1.572	1.987	2.793	1.639
Market Capitalization	202.8	344.4	355.9	206.2	97.42	241.4
Sales	111.4	333.1	372.2	239.6	104.5	232.2
PPENT	55.31	103.2	87.84	33.25	7.012	57.33
Book Assets	189.6	374.6	385.7	202.3	85.24	247.5
Book to Market Ratio	0.636	0.758	0.765	0.708	0.622	0.698
Profitability	0.069	0.120	0.125	0.123	0.102	0.108
Market Leverage	0.242	0.300	0.307	0.289	0.267	0.281
R&D to Sales Ratio	0.112	0.051	0.044	0.052	0.065	0.064
SGA to Sales Ratio	0.317	0.251	0.239	0.260	0.283	0.270

Notes: This table reports the characteristics of firms sorted into five portfolios based on their industry-adjusted *mpk*. Firms are formed into portfolios annually by their (de-meaned by industry-year) *mpk*, for those industry-years with at least 10 firms. We compute the median value for each characteristic for each portfolio in each year, and then average those portfolio medians over time. The stock variables (market capitalization, sales, ppent, book assets) are in millions of 2009 dollars, deflated by the annual CPI. All other variables are ratios. R&D is research and development expenses from Compustat, while SGA is sales, general, and administrative expenses, a measure often associated with intangible capital. Further details on our computation of these measures can be found in appendix A.1.

Portfolio sorts - robustness. Table 12 reports two additional measures of excess returns across portfolios. The first, r_{t+3}^e computes three year ahead excess returns (compared to one-year ahead in Table 1). The second, r_{t+1}^a computes one year ahead unlevered returns, which we calculate using an unlimited liability model: $r_{t+1}^a = \frac{Mktcap}{Mktcap+Debt} r_{t+1}^e$. The differences in high versus low MPK portfolio returns are robust to these alternatives (for example, the return to the MPK-HML portfolio continues to be both economically and statistically significant, ranging from about 2% to 3.5%).

Table 13 reports the results of the portfolio sorts across 10, rather than 5, portfolios. We report contemporaneous returns, r_t^e, one year ahead returns, r_{t+1}^e, three year ahead returns, r_{t+3}^e and one year ahead unlevered returns, r_{t+1}^a. Across these various alternatives, there are significant differences between low and high MPK portfolios. The MPK-HML spread ranges from over 3.5% for unlevered within-industry returns to almost 11% for contemporaneous returns.

Table 12: Excess Returns on MPK-Sorted Portfolios – Robustness

Portfolio	Low	2	3	4	High	MPK-HML
			Panel A: Not Industry-Adjusted			
r^e_{t+3}	9.63***	12.43***	12.69***	13.90***	12.99***	3.36*
	(2.96)	(3.69)	(3.71)	(3.81)	(3.38)	(1.96)
r^a_{t+1}	4.64*	7.53***	8.69***	8.66***	8.22***	3.58***
	(1.88)	(3.07)	(3.53)	(3.26)	(3.02)	(3.05)
			Panel B: Industry-Adjusted			
r^e_{t+3}	11.95***	12.27***	12.04***	12.60***	13.82***	1.87**
	(2.99)	(3.71)	(3.75)	(3.60)	(3.58)	(2.22)
r^a_{t+1}	6.86**	7.16***	8.04***	8.17***	8.84***	1.97***
	(2.13)	(2.94)	(3.37)	(3.15)	(3.04)	(2.66)

Notes: This table reports stock market returns for portfolios sorted by mpk. r^e_{t+3} denotes equal-weighted annualized monthly excess stock returns (over the risk-free rate) measured from July of year $t+3$ to June of year $t+4$. r^a_{t+1} denotes equal-weighted unlevered ("asset") returns from from July of year $t+1$ to June of year $t+2$, where we use an unlimited liability model to unlever equity returns. Industry adjustment is done by demeaning mpk by industry-year and sorting portfolios on de-meaned mpk, where industries are defined at the 4-digit SIC code level. t-statistics in parentheses, computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, Table 14 reports the results of portfolio sorts after controlling for firm size and book-to-market. To control for size, we allocate in each industry-year (so all sorts are industry-adjusted) by market capitalization. We then demean each firm's mpk by the mean of their industry-year-size group and sort firms into five portfolios based on this measure. We report the results in the top panel of Table 14. The table shows that even when controlling for size, high MPK firms tend to offer higher expected returns than low ones. We follow a similar procedure to control for book-to-market and report the results in the bottom panel of the table. Again, the spreads in expected returns remain after controlling for this variable.

As a second approach to controlling for these variables, Tables 15 and 16 display the results from double-sorting on MPK and size and book-to-market, respectively. To ensure that there are a sufficient number of firms in each portfolio, we use three portfolios along each dimension. The portfolios are ranked from low to high MPK along the columns and from small to large along the rows. We calculate the MPK-HML spread as well as the small-minus-big spread (the size premium). The left-hand panel reports unconditional expected returns and the right-hand panel after adjusting for industry. Reading across the rows, the table shows that within each size bin, high MPK firms tend to offer higher expected returns than low ones (although the spread is not always statistically significant, which may be a function of (a) either a small number of firms in some of the portfolios or (b) the fact that size and MPK tend to be correlated, e.g., Table

Table 13: Excess Returns on MPK-Sorted Decile Portfolios

Portfolio	Low	2	3	4	5	6	7	8	9	High	MPK-HML
					Panel A: Not Industry-Adjusted						
r_t^e	5.71*	8.30**	8.96**	9.21***	9.86***	11.48***	11.45***	12.56***	14.09***	16.42***	10.72***
	(1.66)	(2.29)	(2.44)	(2.59)	(2.77)	(3.07)	(3.01)	(3.15)	(3.45)	(3.92)	(4.57)
r_{t+1}^e	6.89*	10.34***	11.59***	12.96***	13.17***	13.77***	13.95***	13.52***	13.14***	13.82***	6.95***
	(1.94)	(2.92)	(3.21)	(3.71)	(3.77)	(3.80)	(3.73)	(3.48)	(3.25)	(3.43)	(3.10)
r_{t+3}^e	8.01**	11.30***	12.46***	12.37***	12.53***	12.86***	14.05***	13.73***	12.97***	13.01***	5.00**
	(2.48)	(3.32)	(3.61)	(3.72)	(3.67)	(3.72)	(3.84)	(3.74)	(3.35)	(3.38)	(2.19)
r_{t+1}^a	3.61	5.66**	6.89***	8.17***	8.35***	9.02***	8.73***	8.59***	8.19***	8.25***	4.64***
	(1.40)	(2.31)	(2.76)	(3.34)	(3.46)	(3.56)	(3.35)	(3.14)	(2.89)	(3.11)	(3.07)
					Panel B: Industry-Adjusted						
r_t^e	6.88	7.16*	8.71**	9.12***	9.96***	11.22***	11.83***	12.72***	13.88***	17.71***	10.83***
	(1.45)	(1.83)	(2.40)	(2.62)	(2.83)	(3.23)	(3.27)	(3.30)	(3.41)	(3.98)	(8.04)
r_{t+1}^e	9.18*	13.00***	11.78***	11.31***	12.22***	13.20***	12.14***	13.27***	13.89***	13.48***	4.29***
	(1.95)	(3.33)	(3.32)	(3.34)	(3.65)	(3.80)	(3.42)	(3.54)	(3.53)	(3.16)	(3.24)
r_{t+3}^e	11.20**	12.68***	11.84***	12.68***	12.00***	12.08***	12.43***	12.76***	12.93***	14.81***	3.61***
	(2.50)	(3.47)	(3.53)	(3.85)	(3.72)	(3.72)	(3.62)	(3.51)	(3.43)	(3.68)	(2.68)
r_{t+1}^a	5.12	8.59***	7.21***	7.10***	7.67***	8.41***	7.72***	8.56***	9.00***	8.66***	3.53***
	(1.39)	(3.01)	(2.88)	(2.97)	(3.27)	(3.42)	(3.05)	(3.21)	(3.23)	(2.82)	(2.99)

Notes: This table reports stock market returns for portfolios sorted by mpk. r_t^e denotes equal-weighted contemporaneous annualized monthly excess stock returns (over the risk-free rate) measured in the year of the portfolio formation from January to December of year t. r_{t+1}^e denotes the analogous future returns, measured from July of year $t+1$ to June of year $t+2$. r_{t+3}^e denotes future returns further in the future, measured as returns from July of year $t+3$ to June of year $t+4$. r_{t+1}^a denotes equal-weighted unlevered ("asset") returns from from July of year $t+1$ to June of year $t+2$, where we use an unlimited liability model to unlever equity returns. Industry adjustment is done by de-meaning mpk by industry-year and sorting portfolios on de-meaned mpk, where industries are defined at the 4-digit SIC code level. t-statistics in parentheses, computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

11). Table 16 reports analogous results using book-to-market, along with the high-minus-low spread (the value premium). Our findings are similar – high MPK firms offer higher expected returns than low ones. The MPK-HML spread is positive within each book-to-market bin and is generally large and statistically significant.

I.2 Adjusting Standard Errors for Generated Regressors

Table 2 reports standard errors that are two-way clustered by firm and industry-year, but do not account for the error coming from the estimation of betas. To see whether this latter source of error would significantly change the standard errors, Table 17 reports standard errors that are block-bootstrapped only on time and account for the estimation error in betas.[67]

To implement this procedure, we use a more restricted sample that includes only non-overlapping periods for estimates of beta. For example, we use quarterly data from five year periods (1990-1995,1996-2000,...) to predict the respective year ahead mpk (in 1996, 2001,...). We then block bootstrap by time within each window a two-stage procedure that first estimates

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[67]Parametric methods of accounting for the error coming from the generated regressors are made difficult by the fact that we have hundreds of thousands of estimated objects – betas for each firm at each point in time.

Table 14: Excess Returns on MPK-Sorted Portfolios Controlling for Size and Book-to-Market

Portfolio	Low	2	3	4	High	MPK-HML
	Panel A: Industry and Market Cap Adjusted					
r^e_{t+1}	12.18***	12.51***	12.95***	13.61***	14.70***	2.52**
	(2.60)	(3.29)	(3.67)	(3.56)	(3.40)	(2.12)
	Panel B: Industry and Book-to-Market Adjusted					
r^e_{t+1}	9.55**	10.44***	11.03***	12.77***	13.24***	3.70***
	(2.03)	(2.83)	(3.11)	(3.37)	(3.04)	(2.60)

Notes: This table reports stock market returns for portfolios sorted by *mpk*. Panel A contains *mpk*-sorted future excess returns after de-meaning by firms of similar market capitalization within the same industry. We split firms in each year-industry into three groups based on their market capitalization and then construct *mpk* residuals by subtracting the mean *mpk* of the industry-year-size group from firm *mpk*. We then sort firms into five portfolios based on their residuals. In Panel B we construct the analogue of this procedure using book-to-market ratios instead of market capitalization. We define an industry at the 4-digit SIC code level. We compute equal-weighted forward annualized monthly excess stock returns (over the risk-free rate), measured in the year following the portfolio formation, from July of year $t+1$ to June of year $t+2$. t-statistics in parentheses, computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

betas and then regresses future *mpk* on those estimates.[68] This yields measures of the error from the estimation of the betas alone. We repeat this procedure 200 times. To estimate the error coming from the second stage, we run the second stage regression and estimate robust standard errors clustered by firm and industry-year. We then calculate the total variance of the second stage estimates as the sum of the variances coming from the first and second stages. Importantly, this assumes that the errors from the two stages are independent. This assumption would be violated if the error in the estimate of the generated regressor is correlated with errors in the second stage dependent variable process (*mpk*). This assumption is likely reasonable in the stock return beta regressions, since returns are close to a random walk and so past errors in the returns process are likely uncorrelated with future realizations of *mpk*. For the *mpk* beta regressions, this assumption may be somewhat more problematic, since there may be persistence in the errors in the *mpk* process. If this assumption is violated, the sign of the effect on the standard error is ambiguous.

Table 17 reports both the combined generated-regressor corrected standard error as well as the version computed using only the standard errors from the second stage. Though the standard errors generally increase, the point estimates remain significant across all but one specification (*mpk* betas calculated from a CAPM model; as discussed above, this standard error may be affected by our assumption of independent errors across the two stages). Since

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[68]If we did not restrict the window to non-overlapping samples, we could not block bootstrap by time within each window, as several windows would use the same data point to estimate risk exposures.

Table 15: Excess Returns on MPK and Size Portfolios

Mkt Cap	MPK, Not Industry-Adjusted				MPK, Industry-Adjusted			
	Low	2	High	HML	Low	2	High	HML
Small	15.41***	17.51***	16.75***	1.34	11.20**	12.31***	14.10***	2.90***
	(3.62)	(4.32)	(3.97)	(0.88)	(2.55)	(3.34)	(3.43)	(2.73)
2	8.26**	13.08***	11.76***	3.50**	13.39***	13.77***	14.13***	0.76
	(2.04)	(3.38)	(2.86)	(2.55)	(3.18)	(3.64)	(3.47)	(0.71)
Big	8.39***	10.96***	9.74***	1.35	9.82***	11.01***	11.61***	1.79**
	(2.79)	(3.37)	(2.63)	(0.89)	(2.78)	(3.57)	(3.20)	(2.07)
Small-Big	7.02**	6.55***	7.01***		1.38	1.30	2.49*	
	(2.50)	(2.77)	(2.90)		(0.82)	(0.88)	(1.65)	

Notes: This table reports stock market returns for portfolios, double sorted by *mpk* and market capitalization. We measure equal-weighted forward annualized monthly excess stock returns (over the risk-free rate), measured in the year following the portfolio formation, from July of year $t+1$ to June of year $t+2$. *t*-statistics in parentheses, computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the sample is a subset of the one in Table 2, the coefficient estimates are not identical.

Table 16: Excess Returns on MPK and Book-to-Market Portfolios

B/M	MPK, Not Industry-Adjusted				MPK, Industry-Adjusted			
	Low	2	High	HML	Low	2	High	HML
Low	4.60	9.42**	9.02**	4.43***	7.22*	9.88***	9.74**	2.52***
	(1.07)	(2.49)	(2.09)	(2.96)	(1.81)	(2.91)	(2.44)	(2.60)
2	9.98***	14.77***	14.64***	4.66***	9.79**	11.52***	12.82***	3.03***
	(2.98)	(4.24)	(3.87)	(3.23)	(2.47)	(3.42)	(3.28)	(3.14)
High	14.28***	16.66***	17.21***	2.93*	16.52***	15.60***	18.03***	1.51
	(4.48)	(4.57)	(4.43)	(1.85)	(4.14)	(4.31)	(4.59)	(1.59)
HML	9.68***	7.24***	8.19***		9.30***	5.72***	8.29***	
	(4.31)	(4.48)	(4.78)		(7.84)	(5.28)	(6.87)	

Notes: This table reports stock market returns for portfolios, double sorted by *mpk* and book-to-market ratios. We measure equal-weighted forward annualized monthly excess stock returns (over the risk-free rate), measured in the year following the portfolio formation, from July of year $t+1$ to June of year $t+2$. t-statistics in parentheses, computed using Newey-West standard errors. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Predictive Regressions – Bootstrapped Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{CAPM}	0.226				0.026			
Two-way clustered S.E.	(0.029)				(0.006)			
Bootstrapped S.E.	(0.041)				(0.011)			
β_{FF}		0.164				0.017		
Two-way clustered S.E.		(0.017)				(0.005)		
Bootstrapped S.E.		(0.039)				(0.007)		
$\beta_{CAPM,MPK}$			0.126				0.049	
Two-way clustered S.E.			(0.032)				(0.014)	
Bootstrapped S.E.			(0.060)				(0.033)	
$\beta_{FF,MPK}$				3.131				1.122
Two-way clustered S.E.				(0.328)				(0.152)
Bootstrapped S.E.				(0.913)				(0.475)
Observations	17422	17422	12673	12673	16857	16857	12185	12169
R^2	0.031	0.054	0.007	0.008	0.067	0.074	0.068	0.065
F.E.	No	No	No	No	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	Yes	Yes	Yes

Notes: This table reports the results of a panel regression of year-ahead *mpk* regressed on measures of firm exposure to aggregate risk. Each observation is a firm-year. F.E. denotes the presence of industry-year fixed effects.