The Asset Durability Premium

Dun Jia, Kai Li, and Chi-Yang Tsou*

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Abstract

Our paper examines the significant asset pricing implications of asset durability for understanding equity risk. We develop a quantitative model with aggregate uncertainty where firms optimize over asset durability driven by occasionally binding borrowing constraints. Our model highlights a novel risk premium channel emerging in general equilibrium, with durable capital harder to finance not only due to its greater down payment, but because of its larger price risk sensitivities to financial frictions. As firms' holding less durable capital provides hedging against aggregate risk, properties of capital prices of different asset durabilities affect the firm risk. Our model helps rationalize the asset durability premium documented in the cross-section of stock returns among financially constrained firms.

JEL Codes: E2, E3, G12

Keywords: asset durability; financial constraints; collateral; cross-section of stock returns

*Dun Jia (dun.jia@phbs.pku.edu.cn), Peking University HSBC Business School; Kai Li (kaili825@gmail.com), Peking University HSBC Business School and the Sargent Institute of Quantitative Economics of Finance; and Chi-Yang Tsou (chi-yang.tsou@manchester.ac.uk), Alliance Manchester Business School, University of Manchester. We thank Hengjie Ai, Frederico Belo (EFA discussant), Utpal Bhattacharya, Hui Chen, Ethan Chiang (TFA discussant), Yongqiang Chu, Ilan Cooper, Andrei Gonçalves (MFA discussant), Vidhan Goyal, Foti Grigoris (FMA discussant), Zhiguo He, Yan Ji, Tse-Chun Lin, Xiaoji Lin (FIRS discussant), Ding Luo (FMA discussant), David Mauer, Adriano Rampini, Roberto Steri, Jincheng Tong, Jialin Yu, and Chu Zhang, as well as seminar participants at the BI Norwegian Business School, Hong Kong University of Science and Technology, Peking University HSBC Business School, University of Amsterdam, University of Bath, University of Liverpool, University of Manchester, University of North Carolina Charlotte, Banque de France, SJTU-UCL Macro-finance Workshop 2019, 2nd Frontiers of Factor Investing Conference, NCTU International Finance Conference 2020, AEA Annual Meeting 2021, MFA Annual Meeting 2020, FMA 2020 and 2022, FIRS Annual Meeting 2021, EEA-ESEM 2021, TFA Annual Meeting 2021, 2022 North American Summer Meeting, 2022 NYCU Summer Workshop in Finance, TFA Corporate Finance Symposium 2022, the 4th Warsaw Money-Macro-Finance Conference, and the EFA Annual Meeting 2024 for their helpful comments. Kai Li gratefully acknowledges the General Research Fund of the Research Grants Council of Hong Kong (Project Number: 16502617) for its financial support. Chi-Yang Tsou gratefully acknowledges the AMBS Research Office for the research support funds. The usual disclaimer applies.

1 Introduction

In this paper, we examine the asset pricing implications of the fact that firms endogenously react to financial constraints by optimizing their capital composition of different asset durabilities, with respect to how much they hold durable vs. non-durable capital, whereby the asset durability has been shown an essential feature of capital (Rampini, 2019).[1] We show compositional changes in asset durability not only determine the price cyclicalities of different assets, but significantly shift the firm risk in the cross-section.

The canonical macro-finance model featuring financial frictions predicts that economic downturns lead to deteriorated firms' financial conditions (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). Rampini (2019) shows that tightened financial constraints determine firms' choices over different types of capital characterized by asset durability. Our paper specifically examines the impacts of firms' asset compositional changes driven by financial frictions on the risk sensitivities of different capital prices in general equilibrium. Most importantly, we demonstrate the novelty of our results by showing both empirically and theoretically that firms' asset composition of different asset durabilities, by loading in different risk exposures to financial frictions, affects the firm risk and determines the cross-section of stock returns.

In particular, our general equilibrium model suggests that firms' substitutability over asset durability delivers an important but under-explored *risk-premium* channel, which finds that the equilibrium price of durable capital is more procyclical, and durable capital is therefore riskier than non-durable capital. Our model insights are new in the sense that durable capital is harder to finance not only because it has a greater down payment, as in Rampini (2019), but also because it exhibits extra risk sensitivities to financial frictions relative to non-durable capital. Hence, as firms' holding less durable capital provides hedging against aggregate risk, properties of capital prices of different asset durabilities significantly shift the firm risk.

We first examine the empirical relationship between asset durability and the expected stock returns. Our paper contributes to the literature by providing the first empirical measure of asset durability at the firm level. Specifically, the novelty of our measure lies in the aggregation of the differed durability across refined asset categories of a firm's portfolio, which is derived from the depreciation data in the U.S. Bureau of Economic Analysis (BEA) fixed asset table. The BEA table provides detailed estimates of depreciation rates and net capital stocks at fixed costs, covering a broad array of assets. For each year, we construct the asset-level durability across assets listed in the BEA table, calculating the industry-level asset durability. We then obtain a firm-level measure of asset durability by calculating the value-weighted average of industry-level asset durability indices across the business segments in which the firm operates.

[1] Asset durability is defined as the inverse of the geometric depreciation rate of a given asset type as in Rampini (2019) and the degree of durability varies across asset types. For example, the depreciation rate can be as low as 1 percent for new residential structures, which are identified as more durable capital, whereas the depreciation rate can be as high as 31 percent for computing equipment, as labeled as less durable capital.

Next, we uncover significant heterogeneities in asset durability across firms and show that firms' portfolios shift toward less durable capital if they face tightened financial constraints. Particularly, we document that stock returns in the cross-section are strongly associated with firms' asset durability measures, especially when firms are financially constrained. In specific, we construct five portfolios that are univariate-sorted based on firms' asset durability relative to their industry peers and then examine the return differences across different portfolios. We show there is a statistically significant asset durability return spread among financially constrained firms. The levered return spread between the highest durability quintile portfolio and the lowest durability quintile portfolio averages approximately 3.56% to 6.93% per year, depending on the specific measure that we use to sample financially constrained firms. Considering the fact that constrained firms with larger asset durability are on average more leveraged in the data, we find that the return spreads between the highest and the lowest durability quintile are still sizeable ranging from 2.34% to 4.75% even after controlling for the leverage effect. Hence, termed as the "Asset Durability Premium", our documented return spread captures differences in average portfolio returns between the highest and lowest portfolios sorted by the asset durability measure, regardless of the leverage ratio differences across portfolios. We show that implementing a high-minus-low strategy based on asset durability spread results in an annualized Sharpe ratio of 0.59 and 0.49 for levered and unlevered returns respectively, comparable to that of the market portfolio. By contrast, we find no asset durability spread among unconstrained firms.

Our model then builds upon our documented empirical regularities in order to rationalize the asset durability premium. In specific, we develop a quantitative general equilibrium model with aggregate uncertainty that allows firms grappling with tightened financial constraints during recessions to adjust the composition of durable and non-durable capital through financing. In our model, firms are ex-ante homogeneous and ex-post heterogeneous in idiosyncratic productivity realizations but subject to occasionally binding borrowing constraints. At the aggregate level, firms' profits are affected by aggregate productivity shocks along with financial shocks that unexpectedly liquidate firms' net worth. Importantly, firms pose capital as collateral to incur external debt financing (e.g., Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010)), which reflects the presence of financial frictions by which lending contracts can not be fully enforced. In line with Rampini (2019), our model distinguishes between durable and non-durable capital with respect to their geometric depreciation rates while both capital types are collateralizeable for financing. However, differed from Rampini (2019) that studies the trade-off between choosing durable and non-durable capital under financial frictions in partial equilibrium, our model focuses on the asset pricing implications of such trade-off in a dynamic and stochastic framework featuring the general equilibrium. We show the general equilibrium effect arises such that firms' choices of asset durability affect both the price riskiness of capital over business cycles and the stock returns across firms in the cross-section.

At the aggregate level, our model suggests that firms become more financially constrained under adverse aggregate productivity shocks and financial shocks, and shift asset holdings toward cheaper and less durable capital. In equilibrium, the price of more durable capital is very procyclical, thus riskier than less durable capital. Consequently, more durable capital commands higher risk compensation as expected returns. Importantly, we stress that this result partly follows from Rampini (2019), as acquiring more durable capital incurs a larger down payment despite of a lower frictionless user cost, which makes it harder to finance. In addition, our general equilibrium model insight is new in that durable capital is more costly also because of its larger price risk sensitivities to aggregate uncertainty. Most importantly, while firms with low net worth but high financing needs endogenously acquire less durable assets, heterogeneities in productivity and net worth then translate into endogenous cross-firm heterogeneities in capital composition of different asset durabilities. In the cross-section, firms with larger asset durability therefore earn higher risk premia. We demonstrate that such cross-sectional variations in firms' portfolio holdings are critically important for understanding the riskiness of financially constrained firms.

Quantitatively, our model, once calibrated to match both standard U.S. business cycle moments and different depreciation rates of more durable and less durable capital in the data, generates the subsitutability between capital types and the relative cyclicality of capital prices. Our model finds that when firms are financially constrained, they hold 2.8% less on durable capital and invest 2.5% less through acquiring durable capital relative to non-durable capital on average. In addition, we find that the price of durable capital is about three to four times more volatile than that of non-durable capital over business cycles as measured by unconditional price volatility or by the covariance between capital prices and the stochastic discount factor. Finally, we show that the riskiness of capital prices determines the firm risk given firms' portfolio heterogeneity in asset durability. Through cross-sectional simulation, our model exhibits extra riskiness for firms' holding durable capital and generates a levered (unlevered) return spread between the highest durability quintile portfolio and the lowest durability quintile portfolio at 4.34% (1.32%) annually, which explains at least about 80% (30%) of observed spreads in our data.

In particular, we emphasize that the asset durability is not a standalone "risk factor" that generates the cross-section pattern of stock returns in our model. Rather, our model predicts that the price of durable capital is much riskier than that of non-durable capital in terms of its risk exposure to financial frictions, which is the key source of risk that is priced in general equilibrium. The cross-section of stock returns is an outcome of heterogeneous firms holding different asset compositions of durable and non-durable capital on balance sheet, which then determines the distribution of equity risk across firms.

Importantly, our model nests and differentiates two offsetting channels that affect firms' substitutability over asset durability and the cross-section of stock returns. First, there is the risk premium channel highlighted in this paper, where durable capital is riskier due to its more procyclical equilibrium price. Second, the asset collateralizability channel, as discussed by Ai, Li, Li, and Schlag (2020a), indicates that financing non-durable capital is riskier because it lacks the collateralizability value. Empirically, we show in Subsections 2.3 and 2.4, by distinguishing between levered and unlevered returns, that firms holding more durable capital are riskier, even after controlling for the asset collateralizability channel that these are also more leveraged firms. In Section I.1.3 of Internet Appendix, we document additional firm-level evidence that controlling for both leverage and the collateralizability measure, i.e., the relative weight of the present value of the Lagrangian multipliers in the total value of the firm's assets as in Ai, Li, Li, and Schlag (2020a), firms with greater asset durability are significantly risker. Theoretically, we derive a clear decomposition from our model in Subsection 4.2 to illustrate these offsetting channels and then discuss why firms' leverage can be an confounding factor for delivering the asset durability premium in Subsection 4.3. Our quantitative exercises find that the newly documented risk premium channel dominates, which delivers a pronounced general equilibrium price effect that increases the relative riskiness of more durable capital.

Importantly, we highlight three important features of our model. First, our model specifically focuses on the margin of firms' acquiring capital via asset purchase in response to financial frictions, leading to changes of capital composition. This differs from another margin by which firms can take leased capital when they are financially constrained (Rampini and Viswanathan, 2013b; Li and Tsou, 2019). Intentionally shutting down the leasing channel, our model is able to disentangle a risk-premium channel that involves firms adjusting the capital mix with purchased capital. Empirically, we provide the evidence showing that firms' adjusting capital mix with purchased capital under financial frictions significantly affect the asset durability and capital prices even controlling for the leasing channel. Second, we stress that in line with Rampini (2019), the durability differences across asset types are fully captured by the varied depreciation rates. Non-durable capital is not associated with those of low quality or low productivity. For example, the differences between the multi-year licensed software and one-year licensed software suggest that the capital goods can be equally productive but operate in varied duration. Importantly, this exactly motivates our model choices of treating durable and non-durable capital as perfect substitutes in firms' production. Third, rather than imposing an always binding constraint, we solve the model with a global solution. This enables us to directly compare and contrast the firm riskiness with and without financial constraints, which better connects our model with the empirical facts.

Based on our model, we continue to provide additional empirical tests in support of our theoretical assumptions and results. To best connect our quantitative model predictions with the data, in the spirit of Eisfeldt and Muir (2016) and Belo, Lin, and Yang (2018), we adopt a model-guided approach to first estimate the underlying unobserved financial shocks from the data. We obtain the proxy for financial shocks using a multivariate regression that is disciplined by the key mechanisms of the model. Specifically, we first identify two key model moments: the change in the aggregate debt-to-net worth ratio of firms and the spread between the shadow interest rate and the risk-free rate, which combined help explain most of the variation of financial shocks in the model up to 78% as measured by R^2 in a regression setting. With the estimated regression coefficients, we then generate a time series of model-implied financial shocks based on the empirical correspondences of these two moments.

With our estimated financial shock series, we document additional important empirical results. First, our model predicts that durable assets are more expensive than non-durable assets, not only due to higher down payments but also larger risk sensitivities and price volatilities over business cycles. We present direct evidence that illustrates the variance in price cyclicality and show in Section 6.1 that capital price of more durable assets displays greater sensitivity to the model-implied financial shocks reflective of the degree of financial frictions. Second, with respect to the substitutability between asset durabilities highlighted in our model, we further show that the durability of financially constrained firms is lower whereas that of financially unconstrained firms increases given adverse financial shocks, suggesting constrained firms are shifting the asset portfolio toward cheaper, less durable assets when borrowing constraints are tightened. Such evidence further confirms our main model mechanism that firms respond to financial constraints by adjusting their capital mix, leading to risk differences across firms.

In addition, we empirically assess the riskiness of asset-durability-sorted portfolios by estimating a two-factor asset pricing model that includes both aggregate stock market returns and our model-implied financial shocks. Our findings show that firms with higher asset durability experience a more pronounced decline in cash flows following bad financial shocks. Next, we implement a generalized method of moments (GMM) estimation of Cochrane (2005) to test the price of macroeconomic risk and the exposure to such risk of asset-durability-sorted portfolios. Our two-factor model captures reasonably well the variation in the average returns of the asset-durability-sorted portfolios, and we find that the price of risk with respect to the financial shocks is significantly negative, consistent with our model prediction. Moreover, GMM-implied alphas (i.e., pricing errors) in the high-minus-low spread portfolio sorted on asset durability are not statistically significant. Finally, the goodness of fit of our two-factor model is driven by the increasing negative exposure of the high-durability portfolios to financial shocks. We conduct similar tests using simulated data from our quantitative model. We show the price of risk with respect to the financial shocks is negative and statistically significant, more importantly, much well aligned with the empirical findings. Taken together, high-asset-durability firms exhibit higher expected stock returns because they have negative betas on financial shocks that are negatively priced. This is exactly consistent with our model prediction that firms' asset composition, given different risk exposures driven by asset durability, affects the firm risk and the cross-section of stock returns.

Finally, we rule out alternative explanations for the cross-sectional variation in portfolio returns sorted by asset durability. Conducting asset pricing factor tests, we find that alphas remain significant even after we account for Fama and French (2015) five factors or Hou, Xue, and Zhang (2015) (HXZ hereafter) q-factors. This implies that the positive asset-durability-return relationship cannot be explained by established firm characteristics like size, value, profitability, and investment. Moreover, we show the asset durability premium cannot be explained by the leasing channel (Rampini and Viswanathan, 2013b; Li and Tsou, 2019). Additionally, we employ monthly Fama and Mac-

Beth (1973) regressions to assess the ability of firm-level durability to predict cross-sectional stock returns. This approach allows us to control for an extensive list of firm characteristics that typically predict stock returns. The slope coefficient associated with a firm's lagged durability is both economically and statistically significant. For instance, controlling for firms' financial leverage, a one-standard-deviation increase in a firm's durability corresponds to a 2.13% increase in a firms' expected stock return. We then confirm that the positive durability-return relation is not driven by other known predictors correlated with the durability measure. Specifically, we consider potential confounding effects associated with capital collateralizability, operating leverage and adjustment costs, output durability, and financial distress.[2] Our estimation results all suggest that the asset-durability-return relation persists even when we control for firm characteristics associated with these channels.

Related Literature. First, our paper builds on the corporate finance literature that emphasizes the importance of collateral for firms' capital structure decisions. Albuquerque and Hopenhayn (2004) study dynamic financing with limited commitment. Rampini and Viswanathan (2010, 2013a) develop a joint theory of capital structure and risk management based on firms' asset collateralizability. Schmid (2008) considers the quantitative implications of dynamic financing with collateral constraints. Nikolov, Schmid, and Steri (2021) meanwhile examine the quantitative implications of various sources of financial frictions on firms' financing decisions, including the collateral constraint. Falato, Kadyrzhanova, Sim, and Steri (2022) provide empirical evidence for the link between asset collateralizability and leverage in aggregate time series and in the cross-section. Our paper departs from these papers in that we explicitly study firms' optimal asset acquisition decisions among assets with different durabilities under the context of an occasionally binding collateral constraint, as in Rampini (2019). However, different from Rampini (2019), we bring the asset durability decision into a general equilibrium framework, take aggregate shocks into accounts, and highlight important asset pricing implications of an underexplored channel for determining the riskiness of equilibrium capital prices and the cross-sectional stock returns.

Second, a rich literature that starts with Eisfeldt and Rampini (2006) has examined how durable assets are reallocated across firms. In this body of research, a consistent empirical observation is that financially constrained agents often engage in the acquisition of assets within secondary markets. Specifically, Eisfeldt and Rampini (2007) examine investment decisions in new and used capital within the context of financial frictions, demonstrating that financially constrained firms tend to prefer older investment goods. Gavazza, Lizzeri, and Roketskiy (2014) explore welfare gains from secondary markets for durable goods, especially with respect to consumer heterogeneity. Lanteri (2018) looks into the market for used investment goods using a quantitative business-cycle model

[2]Existing systematic risks that may explain the documented asset durability premium include collateralizability (e.g., Ai, Li, Li, and Schlag (2020a)), operating leverage and adjustment costs (e.g., Zhang (2005), Gu, Hackbarth, and Johnson (2018), and Kim and Kung (2017)), output durability (e.g., Gomes, Kogan, and Yogo (2009)), and financial distress (e.g., Griffin and Lemmon (2002), Bharath and Shumway (2008), and Campbell, Hilscher, and Szilagyi (2008)).

with firm heterogeneity subject to idiosyncratic productivity shocks. Rampini (2019) examines the effects of asset durability on investment financing in the presence of collateral constraints. Building upon these insights, Hu, Li, and Xu (2020) adjust firms' marginal product of capital (MPK) by considering leased capital, highlighting leasing as an additional channel for capital reallocation that alters patterns of capital misallocation. Gavazza and Lanteri (2021) emphasize the role of secondary markets in reallocating used consumer durable goods from wealthier to poorer households, proposing that this mechanism contributes to the transmission of credit shocks. Meanwhile, Ma, Murfin, and Pratt (2022) utilize a large dataset on equipment transactions and document a negative correlation between firm age and capital age. Lanteri and Rampini (2023) comprehensively evaluate the welfare cost of two types of pecuniary externalities involved in capital reallocation via the resale of old capital. Our paper extends the existing literature by further exploring asset pricing implications of firms' capital choices. In particular, we develop a quantitative general equilibrium model that features firms' endogenous choices over asset durabilities and our findings largely enrich the views that mainly focus on new vs. used capital. For example, two brand new models of machines could differ in their depreciation rates while older capital may have either a longer or shorter duration of remaining service years as compared to newer capital.

Third, our paper also builds on the large macroeconomics literature that studies the role of credit market frictions in generating fluctuations over business cycles (see Quadrini (2011) and Brunnermeier, Eisenbach, and Sannikov (2012) for extensive reviews). The papers most related to ours emphasize the importance of borrowing constraints and contract enforcements, such as Kiyotaki and Moore (1997, 2012), Gertler and Kiyotaki (2010), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and Elenev, Landvoigt, and Van Nieuwerburgh (2021). In addition, Gomes, Yamarthy, and Yaron (2015) study asset pricing implications of credit market frictions in a production economy. Our model examines the impacts of financial shocks on constraining firms' balance sheets occasionally over business cycles, which causes firms to optimally adjust their asset durability. We show that dynamic substitutabilities between durable and non-durable capital not only matter for the riskiness of capital prices in equilibrium, but also shift the cross-section of stock returns.

In addition, our paper contributes to the literature on production-based asset pricing, for which Kogan and Papanikolaou (2012) provide an excellent survey. From a methodological point of view, our general equilibrium model allows for a cross-section of firms with heterogeneous productivities and is related to previous papers including Gomes, Kogan, and Zhang (2003), Gârleanu, Kogan, and Panageas (2012), Ai and Kiku (2013), and Kogan, Papanikolaou, and Stoffman (2017). Compared to these papers, we incorporate financial frictions in our model and study asset pricing implications of firms' occasionally binding collateral constraints. In this regard, our paper is closely related to Ai, Li, Li, and Schlag (2020a), which use a similar model framework and aggregation technique to study cross-sectional stock returns by focusing on the value of asset collateralizeability. They show that more collateralizable assets provide insurance against aggregate shocks by relaxing collateral constraints, especially in recessions when financial constraints become more binding. Our paper differs from Ai, Li, Li, and Schlag (2020a) in two important dimensions. First, our model nests both channels of the down-payment and the collateralizeability trade-offs between durable and non-durable capital. Our model is therefore well equipped to examine the novel risk-premium channel arising in general equilibrium that makes durable capital riskier compared to less durable capital, despite durable capital is allowed to be more collateralizeable. Second, rather than imposing an always binding constraint, our model is however solved globally such that firms' capital financing is constrained only occasionally, which enables us to compare and contrast the model scenarios with and without the binding constraints. Our quantitative model solution then gives us the exact flexibility to examine the general equilibrium effects of firms' changing asset durability triggered by financial frictions over business cycles, which helps isolate the risk-premium channel under-explored in the literature.

Lastly, our paper is also connected to a broader literature linking investment to the cross-section of expected returns. Zhang (2005) provides an investment-based explanation for the value premium. Tuzel (2010) documents a positive relationship between firms' real estate holding and expected returns and proposes an adjustment cost explanation. Li (2011) and Lin (2012) focus on the relationship between R&D investment and expected stock returns. Eisfeldt and Papanikolaou (2013) develop a model of organizational capital and expected returns. Also, Belo, Lin, and Yang (2018) meanwhile study implications of equity financing frictions on the cross-section of stock returns. Importantly, as non-residential real estate may be considered a particular type of durable capital, our paper still complements and differs from Tuzel (2010) in the following regards. First, our key model mechanism operates because firms are subject to occasionally binding borrowing constraints driven by financial shocks, which is the key source of aggregate risk for asset pricing in the cross-section. Our theory and empirics regarding the asset durability premium particularly focus on the financially constrained firms. This differs from the adjustment cost channel in Tuzel (2010) that capital adjustment is risky regardless of the financial frictions, as long as firms can be affected by adverse aggregate productivity shocks. Second, rather than building in the exogenous capital adjustment cost, our model is new by featuring an *endogenous* cost associated with asset compositional changes that necessarily arise from the general equilibrium, i.e., firms optimally shift away from holding durable capital whenever financial constraints are tightened. That is, financing durable capital incurs a larger cost for its higher down-payment and its greater risk exposure to financial frictions. Our model therefore examines a new and different channel considering firms' adjustment of the capital mix so as to rationalize the documented asset durability premium.

The rest of our paper is organized as follows. We summarize our empirical results on the relationship between asset durability and expected returns in Section 2. We introduce a general equilibrium model with occasionally binding collateral constraints in Section 3, and study the asset pricing implications in Section 4. In Section 5, we provide a quantitative analysis of our model and discuss our model results. In Section 6, we provide additional supporting evidence for our model, and then conclude in Section 7. Details on data construction are relegated to Section IV of the Internet Appendix. In Section V of the Internet Appendix, we provide details on our model solution and present additional empirical evidence to establish the robustness of our results.

2 Empirical Facts

In this section, we present empirical evidence demonstrating how financial constraints affect firms' decisions related to asset durability and capital structure. We highlight key findings that underscore the significance of asset durability in shaping the cross-section of stock returns, suggesting the existence of *asset durability premium* among financially constrained firms.

2.1 Measuring Asset Durability

To empirically examine the connection between asset durability and expected returns of stocks, we first develop the measures of asset durability concerning a wide range of assets. In the spirit of Rampini (2019), we measure an asset's durability based on its service life, calculated as the reciprocal of the asset's depreciation rate. Specifically, we construct the measures of asset durability from the Bureau of Economic Analysis (BEA) fixed asset table, which provides detailed estimates for implied depreciation rates and net capital stocks at a fixed cost across non-residential asset categories.[3] In particular, the depreciation rates of different assets are presented in the table by their uses across industries.[4] Our measures are constructed based on a data sample that spans from 1978 to 2016.

Constructing Industry- and Firm-level Asset Durability Measures

Our measures of asset durability capture the service life of both tangible and intangible assets utilized by firms operating across industries. Specifically, we define the asset durability of tangible and intangible assets k used by industry j in year t as the reciprocal of the implied depreciation rate at the asset level provided in the BEA table, referred to as the Asset Durability Score. We then calculate an industry-level asset durability index by value-weighting the durability of individual assets:

$$\text{Asset Durability}^m_{j,t} = \sum_{k \in m} \bar{w}_{k,j,t} \times \text{Asset Durability Score}^m_{k,j,t},\ m \in \{\text{TAN, INTAN}\}, \tag{1}$$

Here, $\text{Asset Durability}^m_{j,t}$ represents the asset durability for industry j in year t. Specifically,

[3]The Bureau of Economic Analysis (BEA) fixed asset table presents the break-down of the implied depreciation rates and net capital stocks by asset categories, encompassing a wide array of industries.

[4]The BEA employs the 1997 North American Industry Classification System (NAICS) for industry classification. For our empirical analysis, we align the 63 BEA industries with Compustat firms using the NAICS codes.

Asset $\text{Durability}^{\text{TAN}}_{j,t}$ and Asset $\text{Durability}^{\text{INTAN}}_{j,t}$ differentiate the measured asset durability of tangible or intangible capital employed in industry j, respectively. $\bar{w}_{k,j,t}$ denotes the proportion of industry j's capital stock attributed to asset k relative to the total capital stock in year t.

We then construct a firm-level metric for asset durability of tangible and intangible capital by calculating the value-weighted average of industry-level asset durability indices across the various business segments in which a firm operates. The asset durability for a firm's tangible (TAN) or intangible (INTAN) capital stock is derived by aggregating the durability of the industry segments in which the firm operates:

$$\text{Asset Durability}^{m}_{i,t} = \sum_{j=1}^{n_{i,t}} \widetilde{w}_{i,j,t} \times \text{Asset Durability}^{m}_{j,t},\ m \in \{\text{TAN, INTAN}\}, \tag{2}$$

where $n_{i,t}$ denotes the number of industry segments the firm operates in during year t, and $\widetilde{w}_{i,j,t}$ represents the proportion of the firm's sales attributed to industry segment j relative to its total sales in year t. Asset $\text{Durability}^{m}_{j,t}$ is the durability of industry segment j in year t, calculated using equation (1) for tangible or intangible assets.

Finally, the firm-level asset durability is derived as follows:

$$\text{Asset Durability}_{i,t} = w^{\text{TAN}}_{i,t} \times \text{Asset Durability}^{\text{TAN}}_{i,t} + (1 - w^{\text{TAN}}_{i,t}) \times \text{Asset Durability}^{\text{INTAN}}_{i,t}, \tag{3}$$

where $w^{\text{TAN}}_{i,t}$ represents the share of tangible capital for firm i in year t over its capital stock, which is measured by the summation of tangible and intangible capital. Specifically, firm's tangible capital is denoted by the PPEGT item in the Compustat and the intangible capital is measured in line with Peters and Taylor (2017).[5]

2.2 Asset Durability and Financial Constraints

We then explore the relationship between a firm's financial constraints and asset durability. In line with Rampini (2019), we confirm that tightened financial constraints decrease firms' asset durability. Specifically, we use four metrics to gauge the extent of a firm's financial constraints: the dividend payment dummy (Farre-Mensa and Ljungqvist (2016), referred to as DIV), the Size-Age index (Hadlock and Pierce (2010), referred to as SA index), the credit rating (Farre-Mensa and Ljungqvist (2016), referred to as Rating), and the Whited-Wu index (Whited and Wu (2006), Hennessy and Whited (2007), referred to as WW index).[6] We conduct the following analyses of regressing the firm-level asset durability measure on a set of firm characteristics with differed financial constraint measures across specifications.

[5]Following Ai, Li, Li, and Schlag (2020a), we capitalize R&D and SGA expenditures using the perpetual inventory method.

[6]In contrast to the dividend payment dummy (DIV), the non-dividend payment dummy (Non-Div) denotes whether a firm does not pay dividends.

[Place Table 1 about here]

Columns (1) to (4) in Table 1 report the coefficient estimates of estimations without other firm-level controls. Meanwhile, columns (5) to (7) present the estimation results of controlled regressions. Our results across columns find that financial constraints reduce firms' asset durability. In particular, the estimated coefficients associated with the non-dividend dummy are negative, though insignificant. Other financial constraint indicators, such as the SA and WW indices, exhibit significantly negative relationships with asset durability. Our estimation results indeed suggest financial conditions significantly affect the firms' decisions regarding the mix of durable and less durable capital. In particular, tightened financial constraints trigger firms' capital substitutabilities such that firms' asset holding is shifted toward less durable capital.

2.3 Asset Durability and Leverage

Considering that durable capital serving as collateral for financing is more collateralizeable (Ai, Li, Li, and Schlag, 2020a), firms with more durable capital may have greater leverage ratios. We present the evidence to confirm that more leveraged firms are holding more durable capital. Nonetheless, we will be explicitly clear in the following sections that the asset return differences associated with asset durability cannot be explained by the leverage differences. Though, we highlight that our model to be presented later helps rationalize the empirical regularities on both return differentials and the leverage ratios.

In Table 2, we report the summary statistics of the firm-level asset durability measure and the leverage for firms in Compustat. As we have shown that firms of lower asset durability are more financially constrained, we therefore compare and contrast the leverage ratios between financially constrained and unconstrained firms first, and then delve into the differences in leverage among financially constrained firms only.

[Place Table 2 about here]

Panel A of Table 2 displays the asset durability measures, the capital depreciation rates, and the book leverage ratios for the financially constrained and unconstrained firm groups.[7] Two key observations emerge. First, the average asset durability among financially constrained firms is much lower at 12.66 (larger capital depreciation rate of 0.17) compared to that of unconstrained firms at 16.54 (lower capital depreciation rate of 0.13). This again confirms the fact that financial constraints are associated with lower asset durability. Second, the average book leverage of constrained firms is 0.24, which is lower than that of the unconstrained firms at 0.33. This implies that financially

[7] Financially constrained firms are identified if they do not pay dividend by the end of June of a year, and unconstrained otherwise, i.e., the dividend payout dummy (Farre-Mensa and Ljungqvist, 2016). We can show the results are very robust if using alternative financial constraint measures, including the SA index, credit rating, and the WW index.

constrained firms subject to external financing frictions are borrowing less, which is consistent with the findings in Ai, Li, Li, and Schlag (2020a) that firms with less collateralizeable capital is under-leveraged. In Panel B of Table 2, we sort the financially constrained firms into five quintiles based on their asset durability relative to peers within the same NAICS 3-digit industry and tabulate the statistics. Notably, we observe significant variability in average asset durability (depreciation), ranging from 7.69 (0.19) in the lowest quintile (Quintile L) to 18.00 (0.11) in the highest quintile (Quintile H). Furthermore, the book leverage exhibits an upward trend as we move from the lowest to the highest asset durability quintile. In summary, we demonstrate that firms' choices over asset durability are closely connected to firms' financing conditions and affect firms' capital structure.

2.4 Asset Durability and Stock Returns

Next, we document the stock return differences in the cross-section associated with asset durability. We show that firms' financial constraints are crucial to disentangle the connection between the asset durability and the expected returns.

Specifically, we examine the average excess returns of five annually sorted portfolios by firms' asset durability, controlling for industry differences.[8] In addition, we look into the return performance of a "high-minus-low" portfolio, which involves adopting a long position in the highest durability portfolio and a short position in the lowest asset durability portfolio. Importantly, we examine both levered and unlevered returns to control for the leverage effects that higher leverage ratio under financial constraints gives higher returns.[9]

[Place Table 3 about here]

In Table 3, we report levered returns in the left panel and unlevered returns in the right panel. Panel A presents results of the portfolio sorting of stocks of financially constrained firms identified by our four different criteria highlighted in Section 2.2, and Panel B shows results for our whole firm sample. Each section of the table displays *annualized* average excess stock returns (E[R]-R_f, relative to the risk-free rate), t-statistics, standard deviations, and Sharpe ratios for different portfolios sorted on asset durability.

[8]Specifically, by the end of June in each year from 1978 to 2017, we sort firms according to their asset durability relative to their peers within the corresponding NAICS 3-digit industries. This classification generates industry-specific breaking points for quintile portfolios for each June. Therefore, the low (high) portfolio encompasses firms with the lowest (highest) asset durability within each industry. Particularly, we eliminate firms with asset values or sales lower than 1 million from our sample, so we minimize the influence of small firms on our findings.

[9]The unlevered return of a firm is defined as its levered return multiplied by one minus its leverage ratio. See further details per equation (46) in Section 4.3. Regarding the return calculations at the portfolio level, monthly returns of a stock are first averaged across the next twelve months (from July in year t to June in year $t+1$) and then value-weighted taking a firm's market capitalization at the time of a portfolio creation for aggregations up to the portfolio.

In the first section of Panel A, among those financially constrained firms identified by the dividend payout dummy (DIV), the annualized average excess return for firms with high asset durability (Portfolio H) exceeds that of firms with low asset durability (Portfolio L) for both levered and unlevered returns. This divergence in returns is both economically substantial and statistically significant. First, regarding the results on the levered returns, we see a positive correlation between asset durability and the stock returns and the return is statistically significant for the long-short portfolio. Specifically, the high-minus-low portfolio exhibits a statistically significant average excess return of 6.93% (t-value of 2.86) and a Sharpe ratio of 0.59. Moving to the other three lower sections of Panel A, we highlight that this premium remains robust under alternative measures of financial constraint. Second, regarding the unlevered returns in the right panel, despite a less steep pattern, the expected excess returns again increase with asset durability across portfolios regardless of the financial constraint measures. Importantly, the unlevered returns of long-short portfolio remain statistically significant though the magnitudes are somewhat smaller reflecting the leverage effects. However, taking the whole sample including both constrained and unconstrained firms, our results in Panel B find that both the levered and unlevered returns for the long-short portfolio are quite small and lack statistical significance. In addition, the pattern that average excess returns increase with asset durability is much weakened.

In summary, we present compelling evidence that average excess returns increase with asset durability. Our results suggest that the return differences associated with asset durability are particularly pronounced among financially constrained firms, even after controlling for variations in leverage across portfolios. We refer to this return spread, driven by asset durability and observed in the long-short high-minus-low (Portfolio H-L) strategy, as the "asset durability premium."

In the following section, we will construct and present a general equilibrium model featuring heterogeneous firms and financial frictions. This model will allow us to quantitatively account for all documented empirical facts, most notably the positive asset durability premium.

3 A General Equilibrium Model

In this section, we describe the model we use for rationalizing the asset durability spread. The aggregate aspect of the model is intended to follow standard macro models with collateral constraints such as in Kiyotaki and Moore (1997) and Gertler and Kiyotaki (2010). Our model further allows for idiosyncratic productivity shocks as well as firms' entry and exit margin, which results in the heterogeneous durability of assets in the cross-section. These model features help deliver quantitatively plausible firm dynamics in order to study the implications of asset durability for the cross-section of equity returns.

3.1 Households

In our model, the representative household with infinite horizon consists of a continuum of workers and entrepreneurs. Workers (entrepreneurs) receive their labor (capital) incomes every period and submit them to the planner of the household, who makes decisions for consumption for all members of the household. Entrepreneurs and workers make their financial decisions separately.[10]

The household ranks the utility of consumption plans according to the following recursive preference as in Epstein and Zin (1989):

$$U_t = \left\{ (1-\beta) C_t^{1-\frac{1}{\psi}} + \beta (E_t[U_{t+1}^{1-\gamma}])^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}},$$

in which β is the time discount rate, ψ is the intertemporal elasticity of substitution, and γ denotes the degree of the relative risk aversion. As we show later in this paper, together with the endogenous growth and long-run risk, the recursive preference in our model generates a volatile pricing kernel and a sizable equity premium as in Bansal and Yaron (2004).

In every period t, the household consumes C_t and purchases $B_{i,t}$ of risk-free bonds from entrepreneur i, from which she will receive $B_{i,t} R_{f,t+1}$ in the next period, in which $R_{f,t+1}$ denotes the risk-free interest rate from period t to $t+1$. In addition, the household receives capital income $\Pi_{i,t}$ from entrepreneur i. We assume that the labor market is frictionless, and therefore the labor income from worker members is $W_t L_t$. The household budget constraint at time t can therefore be written as:

$$C_t + \int B_{i,t} di = W_t L_t + R_{f,t} \int B_{i,t-1} di + \int \Pi_{i,t} di.$$

We let M_{t+1} denote the stochastic discount factor of period t as implied by household optimization. With recursive preference, the stochastic discount factor is denoted as:

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left(\frac{U_{t+1}}{E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}} \right)^{\frac{1}{\psi}-\gamma},$$

and the optimality of the intertemporal saving decisions implies that the risk-free interest rate must satisfy

$$E_t[M_{t+1}] R_{f,t+1} = 1.$$

3.2 Entrepreneurs

There is a continuum of entrepreneurs indexed by i who pursue productive ideas. An entrepreneur who starts at period 0 draws an idea with initial productivity $\bar{z}_0$ and start to operate

[10] Following Gertler and Kiyotaki (2010), we assume that household members make joint decisions on their consumption to avoid keeping the distribution of entrepreneur income as an extra state variable.

with an initial net worth N_0. Under our convention, N_0 is also the total net worth of all entrepreneurs at time 0 as the total measure of all entrepreneurs is normalized to one.

We let $N_{i,t}$ denote entrepreneur i's net worth at time t, and let $B_{i,t}$ denote the total amount of risk-free bond the entrepreneur issues to the household at time t. Thus, the time-t budget constraint for the entrepreneur is given as:

$$q_{d,t}K^{d}_{i,t+1} + q_{nd,t}K^{nd}_{i,t+1} = N_{i,t} + B_{i,t}. \tag{4}$$

In equation (4), we assume that two types of capital, type-d and type-nd, differ in their asset durability; that is, the former capital is more durable, while the latter capital is less durable. For brevity's sake of model description, we simply call the latter the non-durable capital. We denote these two types of capital with a superscript d for durable and nd for non-durable, respectively. These two types of capital depreciate at geometric depreciation rates $\delta_d < \delta_{nd}$ each period, with $\delta_h \in (0,1)$, for $h \in \{d, nd\}$. We use $q_{d,t}$ and $q_{nd,t}$ to denote their prices at time t, respectively. $K^{d}_{i,t+1}$ and $K^{nd}_{i,t+1}$ are the amount of capital that entrepreneur i purchases at time t, which can be used for production over the period from t to $t+1$. We assume that the entrepreneur only has access to risk-free borrowing contracts (i.e., we do not allow for state-contingent debt). At time t, the entrepreneur is assumed to have an opportunity to default on his contract and abscond with $1-\theta$ of both types of capital. Because lenders can retrieve a θ fraction of the type-h capital upon default, we assume entrepreneur's borrowing is subject to an occasionally binding constraint such that:

$$B_{i,t} \leq \theta \sum_{h\in\{d,nd\}} (1-\delta_h)\, q_{h,t}K^{h}_{i,t+1} \tag{5}$$

Following Rampini (2019), we assume that asset durability could well affect the degree of capital collateralizability as captured by $\theta(1-\delta_h)$ as in equation (5).[11] This implies that more durable capital (i.e. lower δ_h) is more collateralizable. In our paper, we highlight that a clear distinction exists between the durability and collateralizability of an asset. According to Ai, Li, Li, and Schlag (2020a), an asset with higher colllateralizability lowers the riskiness of assets as insurance against aggregate shocks by relaxing the financing constraint. However, unlike that of the asset collateralizability, we show that asset durability, which is the key focus of our paper, determines not only the upper bound of capital financing, but also the price of collateralizeable assets. We show that the net effect of asset durability against the collateralizability of an asset means that the price of more durable assets exhibits greater risk sensitivities to aggregate shocks. Therefore in equilibrium, assets with longer durability embody higher riskiness than those with shorter durability.

Let $z_{i,t+1}$ denote entrepreneur i's idiosyncratic productivity. From time t to $t+1$, the produc-

[11]That is, the effective degree of collateralizability for a given type of capital, $\frac{B_{i,t}}{q_{h,t}K^{h}_{i,t+1}}$, when the borrowing constraint is binding is given by $\theta\,(1-\delta_h)$.

tivity of entrepreneur i evolves according to the law of motion:

$$z_{i,t+1} = z_{i,t} e^{\varepsilon_{i,t+1}}, \tag{6}$$

in which $\varepsilon_{i,t+1}$ is a Gaussian shock with mean μ_ε and variance σ_ε^2, assumed to be i.i.d. across agents i and over time. We use $\Pi\left(\bar{A}_{t+1}, z_{i,t+1}, K_{i,t+1}^d, K_{i,t+1}^{nd}\right)$ to denote entrepreneur i's equilibrium profit at time $t+1$ that arises from running a firm for production, in which $\bar{A}_{t+1}$ is the aggregate productivity realized in period $t+1$.[12] We provide the specification of the aggregate productivity process later in Section 5.1.

In period $t+1$, after production, the entrepreneur experiences a financial shock with probability λ_{t+1}, upon which that entrepreneur loses his idea and must liquidate all his net worth $N_{i,t+1}$ and thus cannot continue to the next period.[13] Specifically, if such a liquidation shock hits, then the entrepreneur restarts with a new idea with initial productivity $\bar{z}_{t+1}$ and an initial net worth χS_{t+1}, as a fraction $\chi \in (0,1)$ of the total asset of the economy in period $t+1$, S_{t+1}. The total asset value of the economy is then given by:

$$S_{t+1} = \Pi\left(\bar{A}_{t+1}, K_{t+1}^d, K_{t+1}^{nd}\right) + (1-\delta_d)\, q_{d,t+1} K_{t+1}^d + (1-\delta_{nd})\, q_{nd,t+1} K_{t+1}^{nd} \tag{7}$$

in which $\Pi\left(\bar{A}_{t+1}, K_{t+1}^d, K_{t+1}^{nd}\right)$ denotes the aggregate profit of all entrepreneurs who run firm productions as of period $t+1$. Besides the flow value of total profits, the stock value of both capital types after depreciation also determines the total asset value of the economy.

Conditional on no liquidation shock realized in period $t+1$, the net worth $N_{i,t+1}$ of entrepreneur i at time $t+1$ is determined as:

$$\begin{aligned} N_{i,t+1} &= \Pi\left(\bar{A}_{t+1}, z_{i,t+1}, K_{i,t+1}^d, K_{i,t+1}^{nd}\right) + (1-\delta_d)\, q_{d,t+1} K_{i,t+1}^d \\ &\quad + (1-\delta_{nd})\, q_{nd,t+1} K_{i,t+1}^{nd} - R_{f,t+1} B_{i,t}. \end{aligned} \tag{8}$$

The entrepreneur's net worth is the sum of profit that it receives from firm production and the non-depreciated capital of two types accounting for different depreciation rates δ_h after he pays back the debt borrowed from the last period plus interest. The aggregate net worth through integration over all entrepreneurs therefore satisfies:

$$N_{t+1} = (1-\lambda_{t+1})(S_{t+1} - R_{f,t+1} B_t) + \lambda_{t+1} \chi S_{t+1} \tag{9}$$

Whenever a liquidity shock hits, entrepreneurs submit their net worth to the household who choose consumption collectively for all members, and entrepreneurs then value their net worth using the same pricing kernel as the household. We let V_t^i denote the value function of entrepreneur i.

[12] Therefore, we use firm and entrepreneur interchangeably depending on the context.

[13] This assumption effectively makes entrepreneurs less patient than the household and prevents them from saving their way out of the financial constraint.

It must satisfy the following Bellman equation:

$$V_t^i = \max_{\{K_{i,t+1}^d, K_{i,t+1}^{nd}, N_{i,t+1}, B_{i,t}\}} E_t \left[M_{t+1} \{ \lambda_{t+1} N_{i,t+1} + (1 - \lambda_{t+1}) V_{t+1}^i \} \right], \tag{10}$$

subject to the budget constraint in equation (4), the collateral constraint in equation (5), and the law of motion of $N_{i,t+1}$ given by equation (8).

3.3 Production

Final Output As $z_{i,t}$ denotes the idiosyncratic productivity for entrepreneur i running a firm production at time t, output $y_{i,t}$ of firm i at time t is assumed to be generated through the following production technology:

$$y_{i,t} = \bar{A}_t \left[z_{i,t}^{1-\nu} \left(K_{i,t}^d + K_{i,t}^{nd} \right)^{\nu} \right]^{\alpha} L_{i,t}^{1-\alpha} \tag{11}$$

In our formulation, α is the capital share, and ν is the span of control parameter as in Atkeson and Kehoe (2005). Importantly, in the spirit of Rampini (2019) by which asset durability differences across asset types are specifically associated with the depreciation rate differentials rather than the asset productivity or quality differences, our model treats durable and non-durable capital as perfect substitutes in production without introducing additional margins of differences. We will show that in spite of this simple model setup, our general equilibrium model is able to generate different riskiness of capital prices with respect to aggregate uncertainty.

Entrepreneur i's profit from running this firm at time t, $\Pi\left(\bar{A}_t, z_{i,t}, K_{i,t}^d, K_{i,t}^{nd}\right)$ is given as:

$$\begin{aligned} \Pi\left(\bar{A}_t, z_{i,t}, K_{i,t}^d, K_{i,t}^{nd}\right) &= \max_{L_{i,t}} y_{i,t} - W_t L_{i,t}, \\ &= \max_{L_{i,t}} \bar{A}_t \left[z_{i,t}^{1-\nu} \left(K_{i,t}^d + K_{i,t}^{nd} \right)^{\nu} \right]^{\alpha} L_{i,t}^{1-\alpha} - W_t L_{i,t}, \end{aligned} \tag{12}$$

in which W_t is the equilibrium wage rate, and $L_{i,t}$ is the amount of labor hired by entrepreneur i at time t.

It is convenient to write the profit function explicitly by maximizing labor in equation (12) and using the labor market-clearing condition $\int L_{i,t} di = 1$ to get:

$$L_{i,t} = \frac{z_{i,t}^{1-\nu} \left(K_{i,t}^d + K_{i,t}^{nd} \right)^{\nu}}{\int z_{i,t}^{1-\nu} \left(K_{i,t}^d + K_{i,t}^{nd} \right)^{\nu} di}, \tag{13}$$

so that entrepreneur i's profit function becomes:

$$\Pi\left(\bar{A}_t, z_{i,t}, K_{i,t}^d, K_{i,t}^{nd}\right) = \alpha \bar{A}_t z_{i,t}^{1-\nu} \left(K_{i,t}^d + K_{i,t}^{nd} \right)^{\nu} \left[\int z_{i,t}^{1-\nu} \left(K_{i,t}^d + K_{i,t}^{nd} \right)^{\nu} di \right]^{\alpha-1}. \tag{14}$$

Given the output of entrepreneur i, $y_{i,t}$, from equation (11), the total output of the economy is given as:

$$\begin{aligned} Y_t &= \int y_{i,t} di, \\ &= \bar{A}_t \left[\int z_{i,t}^{1-\nu} \left(K_{i,t}^d + K_{i,t}^{nd} \right)^\nu di \right]^\alpha . \end{aligned} \tag{15}$$

Capital Goods We assume that capital goods are produced from a constant-return-to-scale technology subject to a convex adjustment cost function. That is, capital production, also known as investment, I_t, costs $G\left(I_t, K_t^d + K_t^{nd}\right)$ units of consumption goods. Therefore, the aggregate resource constraint is:

$$C_t + I_t + G\left(I_t, K_t^d + K_t^{nd}\right) = Y_t. \tag{16}$$

We then take the standard assumption that the investment cost function is convex in investment capital ratio $\frac{I_t}{K_t}$ in which total capital stock as of time t, $K_t = K_t^d + K_t^{nd}$. Specifically:

$$G(I_t, K_t^d + K_t^{nd}) = \frac{\tau}{2} \left(\frac{I_t}{K_t^d + K_t^{nd}} - \bar{ik} \right)^2 (K_t^d + K_t^{nd}). \tag{17}$$

$\tau > 0$ is a parameter that indexes the marginal adjustment cost on a capital investment relative to the long-run mean investment capital ratio, $\bar{ik}$.

For tractability of the model, we assume a normalization scheme such that, at the aggregate level, the proportion of two types of capital is fixed, such that $\frac{K_t^d}{K_t} = \zeta$, and $\frac{K_t^{nd}}{K_t} = 1 - \zeta$ for which $\zeta > 0$ leads to a constant ratio of type-d to type-nd capital, $\zeta / (1 - \zeta)$. This assumption helps such that the state of our model economy can be well summarized by a single state variable.[14] In addition to the technical merit, we further discuss the theoretical and empirical relevance of this assumption. First, this assumption helps achieve a nice aggregation across firms without discounting our model insights on the cross-section of stock returns, which is ultimately our key focus. Our model will deliver the simplicity that the equilibrium quantities and prices only depend on the aggregate states rather than the firm distribution. However, our model still maintains a rich cross-section of heterogeneous firms' capital ratios given different idiosyncratic productivities, capital, debt, and net worth positions across firms. The constant capital ratio assumption therefore gives us the leverage to focus on the asset pricing implications of the cross-sectional heterogeneities of firms' asset holdings of different asset durabilities without over-complicating our model dynamics. Second, in Section 6 of additional empirical analysis, we find that financially constrained firms reduce their asset durability given adverse financial shocks whereas unconstrained firms increase their asset durability through capital reallocation. Such evidence squares well with our model assumption

[14] Without this assumption, we must keep track of the ratio of two types of capital as an additional aggregate state variable; thus, we will not be able to achieve the recursion construction of the Markov equilibrium and the aggregation results as shown in Proposition 1.

that the total quantity ratios of durable and nondurable capital at the aggregate level are relatively stable at the business cycle frequency. Finally, given this assumption, we can characterize the fraction of the new investment goods in producing type-d and type-nd capital, ϕ_t and $1-\phi_t$, respectively, such that $\phi_t = (\delta_d - \delta_{nd})\,\zeta\,(1-\zeta)\,\frac{K_t}{I_t} + \zeta$. The aggregate stocks of type-d and type-nd capital are therefore:

$$K_{t+1}^{d} = (1-\delta_d)\,K_t^{d} + \phi_t I_t \tag{18}$$

$$K_{t+1}^{nd} = (1-\delta_{nd})\,K_t^{nd} + (1-\phi_t)\,I_t. \tag{19}$$

4 Equilibrium Asset Pricing

4.1 Aggregation

Our economy is one with both aggregate and idiosyncratic productivity shocks. In general, we use the joint distribution of capital and net worth as an infinite-dimensional state variable in order to characterize equilibrium dynamics recursively. In this section, we follow Ai, Li, Li, and Schlag (2020a) and maintain that the aggregate quantities and prices of our model can be characterized without any reference to firm distribution. Given aggregate quantities and prices, quantities and shadow prices at the individual firm level can be directly computed using equilibrium conditions.

Distribution of Idiosyncratic Productivity At the aggregate level, the heterogeneity of idiosyncratic productivity can be conveniently summarized by a simple statistic: $Z_t = \int z_{i,t} di$. Given the law of motion of $z_{i,t}$ from equation (6) and the fact that entrepreneurs receive a liquidation shock with probability λ_t, we have:

$$Z_{t+1} = (1-\lambda_t)\int z_{i,t} e^{\varepsilon_{i,t+1}} di + \lambda_t \bar{z}_{t+1}.$$

Only a fraction $1-\lambda_t$ of entrepreneurs will survive until the next period, while the rest will restart with productivity of $\bar{z}_{t+1}$ in period $t+1$. As the law of motion of firms' idiosyncratic productivity shocks is time-invariant and that of liquidation shocks are specified as stationary processes, the cross-sectional distribution of $z_{i,t}$ converges to a stationary distribution.[15] We assume that $\varepsilon_{i,t+1}$

[15]In fact, the stationary distribution of $z_{i,t}$ is a double-sided Pareto distribution. Our model is therefore consistent with the empirical evidence regarding the power law distribution of firm size.

is independent of $z_{i,t}$ and can integrate out $\varepsilon_{i,t+1}$ and rewrite the above equation as:[16]

$$\begin{aligned} Z_{t+1} &= (1-\lambda_t) \int z_{i,t} E\left[e^{\varepsilon_{i,t+1}}\right] di \ + \lambda_t \bar{z}_{t+1} \\ &= (1-\lambda_t)\, Z_t e^{\mu_\varepsilon + \frac{1}{2}\sigma_\varepsilon^2} + \lambda_t \bar{z}_{t+1}, \end{aligned} \tag{20}$$

in which the last equality follows from the fact that $\varepsilon_{i,t+1}$ is normally distributed. Clearly, if we choose the normalization $\bar{z}_{t+1} = \frac{1}{\lambda_t}\left[1 - (1-\lambda_t)\, e^{\mu_\varepsilon + \frac{1}{2}\sigma_\varepsilon^2}\right]$ and initialize the economy by setting $Z_0 = 1$, then $Z_t = 1$ for all t. We assume as much for the rest of our paper.

Firm Profits We assume that $\varepsilon_{i,t+1}$ is observed at the end of period t when entrepreneurs plan the next period's capital. As we show in Section III of the Internet Appendix, this implies that entrepreneur i will choose $K_{i,t+1}^{d} + K_{i,t+1}^{nd}$ to be proportional to $z_{i,t+1}$ in equilibrium. Additionally, because $\int z_{i,t+1} di = 1$, we must have:

$$K_{i,t+1}^{d} + K_{i,t+1}^{nd} = z_{i,t+1}\left(K_{t+1}^{d} + K_{t+1}^{nd}\right), \tag{21}$$

in which K_{t+1}^{d} and K_{t+1}^{nd} are the aggregate quantities of type-d and type-nd capital, respectively.

The assumption that capital is chosen after $z_{i,t+1}$ is observed rules out capital misallocation and implies that total output does not depend on the joint distribution of idiosyncratic productivity and capital. This is because given idiosyncratic shocks, all entrepreneurs choose the optimal level of capital such that the marginal productivity of capital is the same for all entrepreneurs. Thus, $Y_t = \bar{A}_t \left(K_t^d + K_t^{nd}\right)^{\alpha\nu} \int z_{i,t} di = \bar{A}_t \left(K_t^d + K_t^{nd}\right)^{\alpha\nu}$. It also implies that the profit at the firm level is proportional to aggregate productivity such that:

$$\Pi\left(\bar{A}_t, z_{i,t}, K_{i,t}^{d}, K_{i,t}^{nd}\right) = \alpha \bar{A}_t z_{i,t}\left(K_t^{d} + K_t^{nd}\right)^{\alpha\nu},$$

and the marginal products of capital are equalized across firms for the two types of capital:

$$\frac{\partial}{\partial K_{i,t}^{d}}\Pi\left(\bar{A}_t, z_{i,t}, K_{i,t}^{d}, K_{i,t}^{nd}\right) = \frac{\partial}{\partial K_{i,t}^{nd}}\Pi\left(\bar{A}_t, z_{i,t}, K_{i,t}^{d}, K_{i,t}^{nd}\right) = \alpha\nu \bar{A}_t \left(K_t^{d} + K_t^{nd}\right)^{\alpha\nu - 1}. \tag{22}$$

To derive equation (22), we take derivatives of firm i's output function in equation (11) with respect to $K_{i,t}^{d}$ and $K_{i,t}^{nd}$, and then impose optimality conditions in equations (13) and (21).

Intertemporal Optimality Having simplified profit functions, we can derive the optimality conditions for the entrepreneur's maximization problem in equation (10). We denote the

[16] The first line requires us to define the set of firms and the notion of integration in a mathematically careful way. Rather than reviewing the technical details, we refer readers to Feldman and Gilles (1985) and Judd (1985). Constantinides and Duffie (1996) use a similar construction in the context of heterogeneous consumers. See footnote 5 in Constantinides and Duffie (1996) for a more careful discussion on possible constructions of an appropriate measurable space under which the integration is valid.

marginal value of net worth for entrepreneur i using μ_t^i and let η_t^i be the Lagrangian multiplier associated with the collateral constraint in equation (5). The first-order condition with respect to $B_{i,t}$ implies:

$$\mu_t^i = E_t\left[\widetilde{M}_{t+1}^i\right] R_{f,t+1} + \eta_t^i, \tag{23}$$

where:

$$\widetilde{M}_{t+1}^i \equiv M_{t+1}[(1-\lambda_{t+1})\,\mu_{t+1}^i + \lambda_{t+1}]. \tag{24}$$

We find that one unit of net worth allows an entrepreneur to reduce one unit of borrowing, the present value of which is $E_t\left[\widetilde{M}_{t+1}^i\right] R_{f,t+1}$, and relaxes the collateral constraint, the benefit of which is measured by η_t^i.

Similarly, the first-order condition for $K_{i,t+1}^d$ is:

$$\mu_t^i = E_t\left[\widetilde{M}_{t+1}^i \frac{\frac{\partial}{\partial K_{i,t+1}^d}\Pi\left(\bar{A}_{t+1}, z_{i,t+1}, K_{i,t+1}^d, K_{i,t+1}^{nd}\right) + (1-\delta_d)\, q_{d,t+1}}{q_{d,t}}\right] + \theta(1-\delta_d)\eta_t^i. \tag{25}$$

It implies that an additional unit of net worth allows an entrepreneur to purchase $\frac{1}{q_{d,t}}$ units of capital, which pays a profit of $\frac{\partial}{\partial K_{i,t+1}^d}\Pi\left(\bar{A}_{t+1}, z_{i,t+1}, K_{i,t+1}^d, K_{i,t+1}^{nd}\right)$ over the next period before it depreciates at rate δ_d. In addition, a fraction θ of type-d capital can be used as collateral to relax the borrowing constraint adjusted for its collateralizability. Similarly, the optimality with respect to the choice of type-nd capital follows:

$$\mu_t^i = E_t\left[\widetilde{M}_{t+1}^i \frac{\frac{\partial}{\partial K_{i,t+1}^{nd}}\Pi\left(\bar{A}_{t+1}, z_{i,t+1}, K_{i,t+1}^d, K_{i,t+1}^{nd}\right) + (1-\delta_{nd})\, q_{nd,t+1}}{q_{nd,t}}\right] + \theta(1-\delta_{nd})\eta_t^i. \tag{26}$$

Recursive Construction of the Equilibrium In our model, entrepreneurs have different levels of net worth. First, net worth depends on the entire history of idiosyncratic productivity shocks, as can be seen from equation (6) by which $z_{i,t+1}$ depends on $z_{i,t}$, which in turn depends on $z_{i,t-1}$ and so forth. Furthermore, net worth also depends on the need for capital, which relies on the realization of the next period's productivity shock. Therefore, the marginal benefit of net worth, μ_t^i, and the tightness of the collateral constraint, η_t^i, generally depend on an individual firm's entire history. We next show that despite the heterogeneity in net worth and capital holdings across firms, our model permits an equilibrium in which μ_t^i and η_t^i are equalized across firms, and that aggregate quantities can be determined independently of the distribution of net worth and capital.

In addition, assumptions that type-d and type-nd capital are perfect substitutes in production and that the idiosyncratic shock $z_{i,t+1}$ is observed before the decisions on $K_{i,t+1}^d$ and $K_{i,t+1}^{nd}$ both greatly simplify our model equilibrium. As a result, the marginal product of both types of capital are equalized within and across firms as shown in equation (22), and μ_t^i and η_t^i are no longer firm-specific according to equations (23) to (26). Intuitively, as the marginal product of capital depends only on the sum of $K^d_{i,t+1}$ and $K^{nd}_{i,t+1}$, entrepreneurs only choose the total amount of capital that equalize marginal product across firms. Depending on the specific borrowing need when $z_{i,t+1}$ is observed before $t+1$, an entrepreneur then determines $K^d_{i,t+1}$ and $K^{nd}_{i,t+1}$ with realized $z_{i,t+1}$ consistent with the firm-specific collateral constraint.

We formalize this observation by constructing a recursive equilibrium in two steps. First, we show that aggregate quantities and prices can be characterized by a set of equilibrium functionals. Second, we further construct an individual firm's quantities from aggregate quantities and prices. We make one final assumption: that aggregate productivity is given by $\bar{A}_t = A_t(K^d_t + K^{nd}_t)^{1-\nu\alpha}$, in which $\{A_t\}_{t=0}^{\infty}$ is an exogenous Markov productivity process. On the one hand, this assumption follows Frankel (1962) and Romer (1986) and is a parsimonious way to generate endogenous growth. On the other hand, this assumption, when combined with recursive preferences, increases the volatility of the pricing kernel, as in the literature on long-run risk models (see, e.g., Bansal and Yaron (2004) and Kung and Schmid (2015)). From a technical point of view, this assumption means that equilibrium quantities are homogenous of degree one in the total capital stock, $K_t = K^d_t + K^{nd}_t$, and equilibrium prices do not depend on K_t. It is therefore convenient to work with normalized quantities.

To begin, we denote a generic variable in current period as X and in future period as X' and then let the lowercase variables denote aggregate quantities normalized by the current total capital stock; for instance, the current period aggregate net worth n denotes aggregate net worth N normalized by the total capital stock K. Abstracting from the time indexation, the equilibrium objects of our model include the normalized consumption, $c\,(A,\lambda,n)$, investment, $i\,(A,\lambda,n)$, the marginal value of net worth, $\mu\,(A,\lambda,n)$, the Lagrangian multiplier on the collateral constraint, $\eta\,(A,\lambda,n)$, the price of type-d capital, $q_d\,(A,\lambda,n)$, the price of type-nd capital, $q_{nd}\,(A,\lambda,n)$, and the risk-free interest rate, $R_f\,(A,\lambda,n)$ as functions of the realized exogenous state variables A and λ, as well as the endogenous state of normalized aggregate net worth, n.

We can define the growth rate of total capital stock as:

$$\Gamma\,(A,\lambda,n) \equiv \frac{K'^d + K'^{nd}}{K^d + K^{nd}} = (1-\delta_{nd}) + (\delta_{nd}-\delta_d)\,\zeta + i\,(A,\lambda,n)$$

Then the law of motion of the endogenous state variable n follows from equation (9):[17]

$$\begin{aligned} n' \quad &= \quad \left(1-\lambda'+\lambda'\chi\right)\Big[\ \alpha A' + \zeta\,(1-\delta_d)\,q_d\,(A',\lambda',n') + (1-\zeta)\,(1-\delta_{nd})\,q_{nd}\,(A',\lambda',n')\ \Big] \\ &\quad -(1-\lambda')\frac{b(A,\lambda,n)R_f(A,\lambda,n)}{\Gamma\,(A,\lambda,n)}. \end{aligned} \tag{27}$$

Given optimal consumption and capital growth rates, we obtain the normalized utility of the

[17]We make use of the property that the ratio of K^d_t over K^{nd}_t is always equal to $\zeta/(1-\zeta)$, as implied by the laws of motion of the capital stock for both types.

household as the functional fixed point of:

$$u(A,\lambda,n)=\left\{(1-\beta)c(A,\lambda,n)^{1-\frac{1}{\psi}}+\beta\Gamma(A,\lambda,n)^{1-\frac{1}{\psi}}\left(E[u(A',\lambda',n')^{1-\gamma}]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right\}^{\frac{1}{1-\frac{1}{\psi}}}.$$

The stochastic discount factors can be rewritten as:

$$M' = \beta\left[\frac{c(A',\lambda',n')\Gamma(A,\lambda,n)}{c(A,\lambda,n)}\right]^{-\frac{1}{\psi}}\left[\frac{u(A',\lambda',n')}{E\left[u(A',\lambda',n')^{1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right]^{\frac{1}{\psi}-\gamma}, \tag{28}$$

$$\widetilde{M}' = M'[(1-\lambda')\,\mu(A',\lambda',n')+\lambda']. \tag{29}$$

We next construct a Markov equilibrium for which all prices and quantities at the aggregate level are functions of the state variables (A,λ,n). For simplicity's sake, we assume that the initial idiosyncratic productivity across all firms satisfies $\int z_{i,1}di=1$, the initial aggregate net worth is N_0, aggregate capital holdings start with $\frac{K_1^d}{K_1^{nd}}=\frac{\zeta}{1-\zeta}$, and a firm's initial net worth satisfies $n_{i,0}=z_{i,1}N_0$ for all i. The full equilibrium of our model then can be characterized as a set of aggregate quantities, $\{C_t,B_t,\Pi_t,K_t^d,K_t^{nd},I_t,N_t\}$, individual entrepreneur choices, $\left\{K_{i,t}^d,K_{i,t}^{nd},L_{i,t},B_{i,t},N_{i,t}\right\}$, and prices $\left\{M_t,\widetilde{M}_t,W_t,q_{d,t},q_{nd,t},\mu_t,\eta_t,R_{f,t}\right\}$ such that, given prices, quantities satisfy the household's and the entrepreneurs' optimality conditions, the market-clearing conditions, and relevant resource constraints. The following proposition provides details regarding the recursive stochastic equilibrium of our model.

Proposition 1. *(Markov Equilibrium)*

Suppose there exists a set of equilibrium functionals $\{c(A,\lambda,n),u(A,\lambda,n),,b(A,\lambda,n),i(A,\lambda,n),\mu(A,\lambda,n),\eta(A,\lambda,n),q_d(A,\lambda,n),q_{nd}(A,\lambda,n),R_f(A,\lambda,n),\phi(A,\lambda,n)\}$ *satisfying the following set of functional equations:*

$$E\left[M'\middle|A,\lambda,n\right]R_f(A,\lambda,n)=1, \tag{30}$$

$$\mu(A,\lambda,n)=E\left[\widetilde{M}'\middle|A,\lambda,n\right]R_f(A,\lambda,n)+\eta(A,\lambda,n), \tag{31}$$

$$\mu(A,\lambda,n)=E\left[\widetilde{M}'\frac{\alpha\nu A'+(1-\delta_d)\,q_d(A',\lambda',n')}{q_d(A,n)}\middle|A,\lambda,n\right]+\theta(1-\delta_d)\eta(A,\lambda,n), \tag{32}$$

$$\mu(A,\lambda,n)=E\left[\widetilde{M}'\frac{\alpha\nu A'+(1-\delta_{nd})\,q_{nd}(A',\lambda',n')}{q_{nd}(A,n)}\middle|A,\lambda,n\right]+\theta(1-\delta_{nd})\eta(A,\lambda,n), \tag{33}$$

$$\frac{n+b(A,\lambda,n)}{\Gamma(A,\lambda,n)}=\zeta q_d(A,\lambda,n)+(1-\zeta)\,q_{nd}(A,\lambda,n), \tag{34}$$

$$\eta(A,\lambda,n)\{b(A,\lambda,n)-\theta[\zeta(1-\delta_d)q_d(A,\lambda,n)+(1-\zeta)(1-\delta_{nd})q_{nd}(A,\lambda,n)]\Gamma(A,\lambda,n)\}=0, \tag{35}$$

$$G'(i(A,\lambda,n))=\phi(A,\lambda,n)\,q_d(A,\lambda,n)+(1-\phi(A,\lambda,n))\,q_{nd}(A,\lambda,n), \tag{36}$$

$$c(A,\lambda,n)+i(A,\lambda,n)+g(i(A,\lambda,n))=A, \tag{37}$$

$$\phi(A,\lambda,n)=\frac{(\delta_d-\delta_{nd})(1-\zeta)\zeta}{i(A,\lambda,n)}+\zeta, \tag{38}$$

where the law of motion of n is given by equation (27), and the stochastic discount factors M' and $\widetilde{M}'$ are defined in equations (28) and (28). Then, equilibrium prices and quantities can be constructed as follows, thereby constituting a Markov equilibrium:

1. *Given the sequence of exogenous shocks $\{A_t,\lambda_t\}$, the sequence of n_t can be constructed using the law of motion in equation (27), and the normalized policy functions are constructed as:*

$$x_t=x(A_t,\lambda_t,n_t),\ \ for\ x=c,u,b,i,\mu,\eta,q_d,q_{nd},R_f,\phi,$$

   and are jointly determined by equations (30)-(38).

2. *Given the sequence of normalized quantities, aggregate quantities are constructed as:*

$$\begin{aligned}K_{t+1}^d&=K_t^d(1-\delta_d)+\phi_tI_t,K_{t+1}^{nd}=K_t^{nd}(1-\delta_{nd})+(1-\phi_t)I_t,\\ X_t&=x_t\left[K_t^d+K_t^{nd}\right],\end{aligned}$$

   for $x=c,i,b,n$, $X=C,I,B,N$, and all t.

3. *Given the aggregate quantities, individual entrepreneurs' net worth follows from equation (8). Given the sequences $\{N_{i,t}\}$, the quantities $B_{i,t},K_{i,t}^d$ and $K_{i,t}^{nd}$ are jointly determined by equations (4), (5), and (21). Finally, $L_{i,t}=z_{i,t}$ for all i,t.*

We first provide the interpretations on our equilibrium conditions. Equation (30) is the household's intertemporal Euler equation with respect to the choice of risk-free asset. Equation (31) is the firm's optimality condition for the choice of debt. Equations (32) and (33) are the firm's first-order conditions with respect to the choice of type-d and type-nd capital. Equation (34) is the budget constraint of firms. Equation (35) governs the condition of complementary slackness, which gives the endogenous upper limit of borrowing for each period. Equation (36) is the optimality condition for capital goods production, equation (37) is the aggregate resource constraint, and equation (38) separates the allocation of new investment into two types of capital.

Proposition 1 implies that conditions in equations (30)-(38) are not only necessary but also sufficient for the construction of equilibrium quantities and prices. This proposition implies that we can solve for aggregate quantities first and then use the firm-level budget constraint and the law of motion of idiosyncratic productivity to construct the cross-section of net worth and capital holdings. Our construction of the equilibrium allows $\eta(A,\lambda,n)>0$ for some values of (A,λ,n); that is, our general setup allows for occasionally binding constraints. Numerically, we resort to the parameterized expectation algorithm as outlined in Christiano and Fisher (2000) and solve the aggregate quantities and prices globally over the permissible domain of state variables.

Importantly, type-d capital can perfectly substitute for type-nd capital in production and both types of capital are freely traded on the market; thus, the marginal product of capital must be equalized within and across firms. The trading of capital therefore equalizes the Lagrangian multiplier of financial constraints across firms. This is the key feature of our model that allows us to construct a Markov equilibrium without including the distribution of capital as a state variable.[18]

4.2 User Cost, Down Payment, and Risk Sensitivity

Following Proposition 1, aggregate quantities and prices do not depend on the joint distribution of individual entrepreneur-level capital and net worth. In this section, we define the user costs of type-d and type-nd capital in the presence of collateral constraint and aggregate risks by extending the definition in Jorgenson (1963). The optimal decision to choose between type-d and type-nd capital is achieved when user costs of two types of capital are equalized. The definitions in this section clarify a novel *risk-premium channel* in equilibrium that affects the relative attractiveness between two types of capital, which has not been emphasized in the literature.

First, we provide the intuition about the trade-off underlying type-d versus type-nd decisions by comparing their user costs. The user cost of capital, $\tau_{h,t}$, $h \in \{d, nd\}$, is:

$$\tau_{h,t} \quad = \quad \vartheta_{h,t} - E_t \left[\frac{\widetilde{M}_{t+1}}{\mu_t} \left\{ q_{h,t+1} \left(1 - \delta_h\right) - R_{f,t+1} \frac{B_{h,t}}{K_{h,t+1}} \right\} \right], \tag{39}$$

We denote $B_{h,t}$ as the act of borrowing for financing type-h capital of amount $K_{h,t+1}$. User costs can be measured by the difference between the minimum down payment per unit of capital paid upfront, $\vartheta_{h,t} = \frac{q_{h,t} K_{h,t+1} - B_{h,t}}{K_{h,t+1}}$, which is the first term in equation (39), and the present value of the fractional capital resale value next period that cannot be pledged, which is the second term in the equation.

For simplicity, we first define a shadow interest rate for borrowing among entrepreneurs, $R_{I,t}$, which is given by:

$$1 = E_t \left(\frac{\widetilde{M}_{t+1}}{\mu_t} \right) R_{I,t+1}. \tag{40}$$

Based on equation (23) and the definition in equation (40), we can obtain an interest rate spread, $\Delta_{f,t+1}$, between two interest rates:

$$\Delta_{f,t+1} = R_{I,t+1} - R_{f,t+1} = \frac{\eta_t}{\mu_t} R_{I,t+1}.$$

Given the occasionally binding constraint as in equation (5), we obtain a measure of aggregate slackness of the credit constraint of each period Δ_t such that:

$$\Delta_t = \theta - \frac{B_t}{[(1-\delta_d) q_{d,t} \zeta + (1-\delta_{nd}) q_{nd,t} (1-\zeta)] K_{t+1}} \geq 0. \tag{41}$$

[18]Because of these simplifying assumptions, our model is not generating a cross-section of firms among which some firms are financially constrained while others are not.

Thus, when all firms are financially constrained in a period, $\Delta_t = 0$.

As a result, we can simplify the user cost of financing for a unit of type-h capital as:

$$\begin{aligned}\tau_{h,t} &= q_{h,t}\left[1-(\theta-\Delta_t)(1-\delta_h)\right] \\ &\quad -(1-\delta_h)\,Cov_t\left(\frac{\widetilde{M}_{t+1}}{\mu_t}, q_{h,t+1}\right) - \frac{1}{R_{f,t+1}+\Delta_{f,t+1}} E_t \varphi_{h,t+1}. \end{aligned} \tag{42}$$

We obtain the second line while the second term in equation (39) is expanded using a covariance term. Factoring out the discount factor $\frac{1}{R_{f,t+1}+\Delta_{f,t+1}}$, the capital resale value for the next period can be summarized as $\varphi_{h,t+1}$ such that:

$$\varphi_{h,t+1} = (1-\delta_h)\left[q_{h,t+1} - R_{f,t+1}(\theta-\Delta_t)\right]. \tag{43}$$

Next, we derive the difference in the user costs of the two types of capital and show that three important wedges appear to drive our main mechanism that determines firms' trade-off between holding type-d and type-nd capital.

$$\tau_{d,t} - \tau_{nd,t} = (\vartheta_{d,t} - \vartheta_{nd,t}) + \Delta_{rp,t} - \frac{1}{R_{f,t+1}+\Delta_{f,t+1}} E_t\left[\varphi_{d,t+1} - \varphi_{nd,t+1}\cdot\right] \tag{44}$$

The first component in equation (44) denotes the down-payment differences highlighted in Rampini (2019), which appears to be positive in the sense that durable capital is more "expensive" for financing a higher down-payment. It directly affects the trade-off for substitution between durable and less durable capital.

Our model, in particular, highlights an *additional* risk-premium wedge as captured by the second term, $\Delta_{rp,t}$. This wedge denotes the difference in the risk premium evaluated by entrepreneurs' stochastic discount factors for type-d versus type-nd capital because of different covariances between capital prices and the discount factor. In particular, this wedge follows that:

$$\Delta_{rp,t} = -(1-\delta_d)Cov_t\left(\frac{\widetilde{M}_{t+1}}{\mu_t}, q_{d,t+1}\right) + (1-\delta_{nd})Cov_t\left(\frac{\widetilde{M}_{t+1}}{\mu_t}, q_{nd,t+1}\right).$$

While substitution across asset durability affects capital prices, such price effects reflect the relative riskiness in general equilibrium, and effectively introduces additional variations to user cost differences across capital types and over time. As a result, this wedge delivers the co-movement of capital prices with stochastic discount factors, which generates risk exposures in stock returns. We show in equilibrium that adverse aggregate productivity and financial shocks tend to trigger severe financial frictions on all firms, and that firms will acquire less expensive and less durable capital. Hence, durable capital not only exhibits greater price cyclicality but its prices are also more sensitive to aggregate shocks. On average, $\Delta_{rp} > 0$ helps explain why durable capital can be considered increasingly more expensive relative to financing for less durable capital (i.e., its incremental risk exposure to aggregate shocks).

Conditional on the same discount factor, the third term in the expectation in equation (44) gives that:

$$E_t\left[\varphi_{d,t+1}-\varphi_{nd,t+1}\right]=(1-\delta_d)\,E_t\left[q_{d,t+1}-R_{f,t+1}(\theta-\Delta_t)\right]-(1-\delta_{nd})\,E_t\left[q_{nd,t+1}-R_{f,t+1}(\theta-\Delta_t)\right],$$

which denotes the difference in the expected capital resale value for the next period. For $\delta_d<\delta_{nd}$ and with higher durable capital price in equilibrium $q_{d,t}>q_{nd,t}$ on average, it can be easily shown that $E_t\left[\varphi_{d,t+1}-\varphi_{nd,t+1}\right]>0$. This term thus reflects the marginal benefit of acquiring durable capital relative to non-durable capital. This relative benefit term partly offsets the higher down payment and greater price riskiness of durable capital to determine total relative user costs between durable and non-durable capital.

In summary, our decomposition exercises suggest that it is costly for a firm to buy durable capital for two reasons. First, acquiring durable capital may be relatively more costly because it requires a larger down payment. Second, given that aggregate shocks will trigger a firm's substitutabilities over asset durability, the greater risk sensitivities of more durable capital relative to that of less durable capital commands a positive risk premium wedge that makes durable capital more expensive in equilibrium. User cost differences that are driven by different down payments have been emphasized in Rampini (2019), while the additional wedge delivered by a risk premium component is a key novel channel that we highlight in our paper.

We then consider a special case that can much highlight our model contribution. Suppose the capital prices of both types are fixed over time; this can be achieved, for instance, if there is no adjustment cost for producing capital goods in our model. It then implies that:

$$\tau_{d,t}-\tau_{nd,t}=(\vartheta_{d,t}-\vartheta_{nd,t})-\frac{1}{R_{f,t+1}+\Delta_{f,t+1}}\left[\varphi_{d,t+1}-\varphi_{nd,t+1}\right].$$

Importantly, in such a case, capital prices do not fluctuate, and risk sensitivities of capital prices do not affect user cost differentials; thus, the risk premium wedge disappears. The asset durability trade-off can be traced back to Rampini (2019), thereby shutting off the risk-premium channel after fixing the stochastic discount factor.

Therefore, we emphasize that our highlighted risk premium channel for affecting choices over asset durability naturally arises in the general equilibrium over business cycles. This premium channel operates as long as more durable capital exhibits greater risk sensitivities to aggregate shocks regardless of whether or not entrepreneurs' financial constraints are binding. It can be shown that down payment differences and relative benefits of resale values of durable capital are both greatly weakened when entrepreneurs' borrowings are constrained. Specifically, according to equation (42), for any given $q_{d,t}$ and $q_{nd,t}$, the binding constraint for $\Delta_t=0$ reduces down payments of $\vartheta_{d,t}$ and $\vartheta_{nd,t}$ on both capital types. The relative marginal benefit of acquiring durable capital is less important as $\frac{1}{R_{f,t+1}+\Delta_{f,t+1}}$ is smaller when the constraint is binding for $\eta_t>0$ and entrepreneurs borrow at a rate with a positive spread $\Delta_{f,t+1} > 0$ over the risk-free rate. With $\Delta_t = 0$, the resale value of both capital goods, $\varphi_{d,t+1}$ and $\varphi_{nd,t+1}$, will be smaller as well. The relative benefit will become less important in determining the substitutabilities of asset durability when adverse financial shocks hit. Hence, on relative terms, the risk-premium channel predominantly affects capital substitutabilities particularly when financial frictions are more severe.

In sum, we use this paper to highlight an additional risk premium channel by building a dynamic choice of asset durability into a general equilibrium model with financial frictions and aggregate risks. We show that because of the different risk sensitivities of durable and non-durable capital over business cycles driven by aggregate shocks, firms' decisions over durable vs. non-durable capital goods are additionally affected by a risk premium channel. More importantly, when financial frictions are more severe than those that bind entrepreneurs' borrowing, this channel is comparatively much stronger and determines firms' choices over asset durability.

4.3 Asset Pricing Implications

In this section, we study the asset pricing implications of our model both at the aggregate and the firm level. It can be shown that the relative price riskiness of durable and non-durable capital naturally translates into a cross-section of stock returns characterized by the firm heterogeneity in asset durability.

Asset Durability Spread at the Aggregate Level We first discuss the importance of differentiating between *levered* and the *unlevered* returns on durable and non-durable capital. Given that one unit of type-h capital costs $q_{h,t}$ in period t and pays off $\Pi_{h,t+1} + (1-\delta_h)\, q_{h,t+1}$ in the next period, for $h \in \{d, nd\}$, unlevered returns therefore follow such that:

$$R_{h,t+1} = \frac{\alpha\nu A_{t+1} + (1-\delta_h)\, q_{h,t+1}}{q_{h,t}} \quad (h = d, nd). \tag{45}$$

The levered return on type-d (type-nd) capital is similarly defined by adjusting for the leverage ratio and net worth:

$$\begin{aligned} R^{Lev}_{h,t+1} &= \frac{\alpha\nu A_{t+1} + (1-\delta_h)\, q_{h,t+1} - R_{f,t+1}(q_{h,t} - n_t/\Gamma_t)}{n_t/\Gamma_t} \\ &= \frac{1}{1-\psi_{h,t}}\left(R_{h,t+1} - R_{f,t+1}\right) + R_{f,t+1}, \end{aligned} \tag{46}$$

in which n_t/Γ_t denotes the amount of internal net worth used to buy one unit of capital of a given type for the period $t+1$, thereby serving as the down payment. The financial leverage ratio specific to that capital type is thus defined as $\psi_{h,t} = \frac{B_{h,t}}{q_{h,t}K_{h,t+1}} = 1 - \frac{n_t}{q_{h,t}\Gamma_t}$. Regarding the first line in equation (46), the numerator captures the next period's return to the type of capital after subtracting the debt financing repayment for buying that one unit of capital. Finally, we see that excess returns derived from levered returns and those of un-levered returns are governed by the following relation:

$$R_{h,t+1}^{Lev} - R_{f,t+1} = \frac{1}{1-\psi_{h,t}}(R_{h,t+1} - R_{f,t+1}). \tag{47}$$

Importantly, when firms' credit constraints are binding, we see that borrowing for acquiring durable capital incurs a greater leverage $\psi_{d,t} = \theta(1-\delta_d) > \psi_{nd,t} = \theta(1-\delta_{nd})$. This generically increases levered returns on financing for durable capital $R_{d,t+1}^{Lev}$ according to equation (46) and follows Ai, Li, Li, and Schlag (2020a) in that more durable capital is more collateralizeable. We therefore report both the levered and the unlevered returns along with their return spreads for asset pricing implications in the following section. Specifically, we show that durable capital indeed has more collateralizeablility value, but is also riskier in equilibrium.

Next, we derive and focus on the spread of expected unlevered returns on durable and non-durable capital investment. Combining the two Euler equations as of equations (32) and (33), we have:

$$E_t\left[\widetilde{M}_{t+1}R_{h,t+1}\right] = \mu_t - \theta(1-\delta_h)\eta_t.$$

and the return spread follows:

$$\begin{aligned}
&E_t\left(R_{d,t+1} - R_{nd,t+1}\right) \\
&= -\frac{1}{E_t\left(\widetilde{M}_{t+1}\right)}\left(Cov_t\left[\widetilde{M}_{t+1}, R_{d,t+1}\right] - Cov_t\left[\widetilde{M}_{t+1}, R_{nd,t+1}\right]\right) - \Omega_t
\end{aligned} \tag{48}$$

in which $\Omega_t = \frac{\theta(\delta_{nd}-\delta_d)}{E_t\left(\widetilde{M}_{t+1}\right)}\eta_t$.

According to equation (48), it shows that the return spread between investing in durable and non-durable capital at the aggregate level is driven by two components: the first term captures the risk premium differences in the covariance of the stochastic discount factor and the asset payoff; the second term gives the return differences due to different marginal gains from financing the durable capital relative to less durable capital for different collateralizablility value of each capital type $\delta_d \neq \delta_{nd}$ when borrowing constraint matters $\eta_t > 0$. Therefore, we label the first component as the risk premium channel, our key focus in this paper, and the second component the collateralizability channel (Ai, Li, Li, and Schlag, 2020a), under both of which more durable and less durable capital would differ in the relative riskiness of prices and the expected returns in equilibrium.

It is critically important to emphasize that equation (48) gives us exactly the very decomposition to compare and contrast the risk-premium and the collateralizability channel, which appear to be offsetting each other. In particular, for the first component, according to equation (45), the main driving force of return spread differences between durable and non-durable capital comes from the resale price $(1-\delta_h)\,q_{h,t+1}$ rather than from the marginal product of capital $\alpha\nu A_{t+1}$, which is common for both capital types. If the price of type-d capital exhibits higher cyclicality, then it is more covaried with the stochastic discount factor and is thus more sensitive to aggregate shocks. As we have discussed previously that this risk-premium channel affects the incentives for firms' optimization over asset durability, $R_{d,t+1}$ is more riskier than its counterpart $R_{nd,t+1}$ over business cycles, and the first term is positive. As for the second term Ω_t, since $\delta_{nd} > \delta_d$, the marginal gain from the collateralizability value of durable capital is positive $\frac{\theta(\delta_{nd}-\delta_d)}{E_t\left(\widetilde{M}_{t+1}\right)} > 0$ as long as the borrowing constraint is binding for $\eta_t > 0$, and the return spread is therefore offset by $\Omega_t > 0$.

By solving our model using a global solution, we are enabled to numerically evaluate the relative magnitudes of these offsetting channels by allowing for occasionally binding constraints over business cycles. It can be shown in later sections that the risk-premium channel is so strong that it dominates the collateralizeability channel when entrepreneurs' are borrowing up to the financial constraints. Therefore, our model results are novel and important, by showing that durable capital is riskier on average in equilibrium even though it has greater collateralizeability value than that of non-durable capital when the credit constraint binds sometimes.

Asset Durability Spread at the Firm Level We then derive model implications on firm risk. We define the equity return on an entrepreneur's net worth to be approximately $\frac{N_{i,t+1}}{N_{i,t}}$.[19] We can use equations (4) and (8) and write out the return as below:

$$\begin{aligned} R_{i,t+1} &= \frac{\alpha\nu A_{t+1}\left(K^{d}_{i,t+1}+K^{nd}_{i,t+1}\right)+(1-\delta_d)\,q_{d,t+1}K^{d}_{i,t+1}+(1-\delta_{nd})\,q_{nd,t+1}K^{nd}_{i,t+1}-R_{f,t+1}B_{i,t}}{N_{i,t}} \\ &= \frac{\vartheta^{i}_{d,t}}{N_{i,t}}R^{Lev}_{d,t+1}+\frac{\vartheta^{i}_{nd,t}}{N_{i,t}}R^{Lev}_{nd,t+1}. \end{aligned}$$

This expression has an intuitive interpretation: the firm's equity return is a weighted average of the levered returns on type-d capital, $R^{Lev}_{d,t+1}$, and the return on type-nd capital, $R^{Lev}_{nd,t+1}$. The weights $\frac{\vartheta^{i}_{d,t}}{N_{i,t}}$ and $\frac{\vartheta^{i}_{nd,t}}{N_{i,t}}$ are the fractions of the down payment for purchasing some amounts of durable capital and non-durable capital, respectively, in entrepreneur i's net worth such that $\frac{\vartheta^{i}_{d,t}}{N_{i,t}}+\frac{\vartheta^{i}_{nd,t}}{N_{i,t}}=1$. Given unlevered returns, it follows that the excess stock returns of firm i can be rewritten as follows:

$$R_{i,t+1}-R_{f,t+1}=\frac{\vartheta^{i}_{d,t}}{N_{i,t}}\frac{1}{1-\psi_{d,t}}(R_{d,t+1}-R_{f,t+1})+\frac{\vartheta^{i}_{nd,t}}{N_{i,t}}\frac{1}{1-\psi_{nd,t}}(R_{nd,t+1}-R_{f,t+1}).$$

Accordingly, as returns $R_{h,t+1}$ and leverages $\psi_{h,t}$ are common across all firms in our model, expected returns differ across firms only because firms' composition of nominal expenditure on type-d versus

[19] In Section III of the Internet Appendix, we recast the firm value in the form of $V^i\left(N_{i,t}, z_{i,t+1}\right) = \mu\left(A_t, \lambda_t, n_t\right) N_{i,t} + \Theta\left(A_t, \lambda_t, n_t\right)\left(K^d_t + K^{nd}_t\right) z_{i,t+1}$. We show $\Theta_t = 0$ when $\nu = 1$ in equation (III.25). As in our calibration, ν is large and close to one, and we ignore the second part in firms' values for illustrative purposes here. In our quantitative evaluations in Section 5, we examine precisely defined returns on firms' equity.

the type-nd capital are different.

Importantly, we demonstrate the very novelty of our model in the sense that firms' asset composition of different asset durabilities, by loading in different risk exposures to aggregate risk, could well affect the firm risk and determine the cross-section of stock returns. Especially, the composition of nominal expenditure on different types of capital can be effectively summarized by the measure of asset durability of a firm in our data. Such parallel between our model and our empirical results allows our model to quantitatively reproduce the asset durability spread that we observe in our data.

5 Quantitative Model Predictions

In this section, we first discuss the calibration of our model and evaluate its ability to replicate key aggregate moments of both macroeconomic quantities and asset prices. We then investigate its performance in terms of quantitatively accounting for key features of firm characteristics and producing the asset durability premium in the cross-section. In particular, we highlight that firms optimally adjust the asset durability on the balance sheet between acquiring durable and non-durable capital over business cycles, which results in different risk sensitivities and price cyclicalities of two capital types in equilibrium. Such a risk-premium channel is the key mechanism that drives return spreads across asset portfolios sorted on asset durability. Importantly, our model finds that although durable capital has greater collateralizability value than non-durable capital, durable capital is much riskier in equilibrium.

5.1 Specification of Aggregate Shocks

We formalize the specification of the exogenous processes of aggregate shocks for our model economy. First, the aggregate productivity in natural logarithm $a \equiv \log(A)$ is:

$$a_t = a_{ss}\left(1 - \rho_A\right) + \rho_A a_{t-1} + \sigma_A \varepsilon_{A,t}, \tag{49}$$

in which a_{ss} denotes the steady-state value of a. In addition, following Ai, Li, and Yang (2020b), we introduce a second type of aggregate shock to the chance that entrepreneurs' net worth will be liquidated, λ_t. This shock originates directly from the financial sector, following Jermann and Quadrini (2012). We incorporate both types of shocks mainly to improve the quantitative performance of our model. As in all standard real business cycle models, it is hard to generate large enough variations in capital prices with just an aggregate productivity shock such that entrepreneurs' net worth is consistent with the data.

Specifically, the shocks to entrepreneurs' liquidation probability directly affect entrepreneurs' discount rate, as can be seen from equation (24), which allows for stronger asset pricing implications.[20] We also note that technically $\lambda_t \in (0, 1)$. For brevity's sake, we set:

$$\lambda_t = \frac{\exp(x_t)}{\exp(x_t) + \exp(-x_t)},$$

and x_t itself follows an autocorrelated process:

$$x_t = x_{ss}(1 - \rho_x) + \rho_x x_{t-1} + \sigma_x \varepsilon_{x,t}.$$

We assume innovations to the two exogenous processes governed by:

$$\begin{bmatrix} \varepsilon_{A,t+1} \\ \varepsilon_{x,t+1} \end{bmatrix} \sim Normal \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{A,x} \\ \rho_{A,x} & 1 \end{bmatrix} \right),$$

in which parameter $\rho_{A,x}$ captures the correlation between these two shocks. Following Quadrini (2011) and Bigio and Schneider (2017), we assume a negative correlation $\rho_{A,x}$ in our calibration, which indicates that a negative productivity shock is associated with a positive discount rate shock. This is partly motivated from structural VAR estimations. In addition, the resource constraint in equation (16) implies a counter-factually negative correlation between consumption and investment growth.[21] Negative correlations of productivity shocks and liquidity shocks are therefore needed in our model framework to quantitatively generate a positive correlation between consumption and investment growth that is consistent with the data.

5.2 Calibration

We calibrate our model to target data moments of annual frequency. To compute these data moments, we use macroeconomic data on a per capita basis from a long sample that ranges from 1930 to 2017. Our consumption, output, and physical investment data are from the Bureau of Economic Analysis (BEA). To complete cross-sectional analyses, we use several data sources at the micro-level that help us evaluate our model predictions, which we summarize in Section IV of the Internet Appendix.

Table 4 reports the list of parameters and the corresponding macroeconomic moments in our calibration procedure. We group our parameters into four blocks. In the first block, we list the parameters that we borrow directly from the literature. In particular, we set the relative risk aversion γ to 10 and the intertemporal elasticity of substitution ψ to 2. These are parameter values in line with the long-run risks literature (e.g., Bansal and Yaron (2004)). The capital share parameter, α, is set to 0.32, close to the number used in the standard RBC literature (e.g., Kydland and Prescott (1982)). The span of control parameter ν is set to 0.85, consistent with Atkeson and

[20] Macro models with financial frictions, as portrayed in Gertler and Kiyotaki (2010) and Elenev et al. (2021), use a similar device for the same reason.

[21] This is a classic problem shared by many neoclassical macroeconomic models with flexible prices. See discussions in Kiyotaki and Moore (2019).

Kehoe (2005). We also set the discount factor $\beta = 0.984$ and the average annual entrepreneur exit probability $E(\lambda) = 0.12$ to jointly match the level of risk-free interest rate for household loans to about 1.2% in the data and set an average firm's life span to 10 years in Compustat. The elasticity parameter of the investment adjustment cost functions is set at $\tau = 7$, which is standard in the RBC literature and allows our model to achieve a reasonably large volatility of investment in line with our data.

[Place Table 4 about here]

We determine the parameters in the second block by matching a set of first moments of quantities and prices to their empirical counterparts. We first set the depreciation rates for durable and non-durable capital to be 0.05 and 0.19, respectively, which correspond to empirical estimates of a lower and upper bound across the refined capital categories that are based on our calculations of the BEA data. We then pick $\zeta = 0.645$, which delivers a total annual depreciation rate of weighted averages of approximately 10%. Given that the average consumption-to-investment ratio $E(C/I)$ is 4, we back out the average economy-wide productivity growth rate $E(A_{ss})$ to match a mean growth rate of the U.S. economy of 2% per year conditional on the depreciation rates of capital. We calibrate the remaining parameters related to financial frictions, namely, the collateralizability parameter, θ, and the transfer to entering entrepreneurs, χ, by jointly matching two moments: the median leverage ratio of 0.31 among U.S. non-financial firms in Compustat and the equity over total asset ratios of approximately 0.48 among younger and newer U.S. private firms aged less than 10 years (Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova, 2018).

The parameters in the third block are based on the conversion of standard parameter values that we estimate using quarterly data. Based on quarterly estimates from Bayesian estimations of a structural model with both macroeconomic and financial blocks (Guerron-Quintana and Jinnai, 2019), we convert quarterly values to their annual counterparts associated with the exogenous processes.[22] The shock correlation is set to $\rho_{A,x} = -0.85$, which lies between the number of -0.75 as derived from the positive correlation between the abundance of credit supply and the aggregate productivity in Bigio and Schneider (2017) and -1 as assumed in Ai, Li, Li, and Schlag (2020a).

The last block contains parameters related to idiosyncratic productivity shocks. We calibrate them to match the mean and standard deviation of the idiosyncratic productivity growth of financially constrained firms in our U.S. Compustat database.

5.3 Numerical Solution and Simulation

We briefly summarize our model's numerical solution in this subsection. In particular, we solve our model globally for aggregate quantities and prices by allowing the credit constraint to be

[22] The persistence parameters are pinned down by having $\rho_A = 0.9543^4 = 0.8294$ and $\rho_x = 0.9870^4 = 0.949$, respectively. The standard deviation of the liquidation shocks and that of the productivity shocks can be obtained such that $\sigma_x = 0.0949 \cdot \sqrt{\sum_{j=0}^{q=3} 0.9870^{2j}} = 0.1862$ and $\sigma_A = 0.0144 \cdot \sqrt{\sum_{j=0}^{q=3} 0.9543^{2j}} = 0.0269$.

binding only occasionally over time. Our numerical analysis involves two major steps. First, we solve the model featuring the aggregate dynamics of quantities and prices. Second, we take the firm's policy functions and simulate a large panel of firms subject to idiosyncratic shocks, so we may compute corporate behaviors and their return profiles across sorted portfolios.

Specifically, we follow Christiano and Fisher (2000) and apply the modified Parameterized Expectation Algorithm (PEA) to directly approximate all expectation terms on the Euler Equations using Chebyshev Polynomials. Conditional on states, the approximated functionals related to policy functions can easily back out the functional values of η_t, which indicate if the credit constraint is binding occasionally. It is important to note that abstracting away from a time-varying firm distribution, our model solution features results that all firms are either constrained at a time or unconstrained at another time along the simulation path. This saves the computational burden if the distribution of firms is a state variable but without sacrificing our model predictability on cross-sectional returns. For a given calibration and our predefined dimension of functional approximation exercises, our model can be solved very quickly and efficiently. We relegate Section II of the Internet Appendix for additional details on our algorithm and implementation.

Once functional approximations are obtained for aggregate quantities and prices, we move to the simulation stage. For each simulation, we simulate the model for 600 periods of 10,000 firms, and drop the first 100 periods of simulated data. We then run 100 separate simulations and compute the averages of data moments aggregated across firms and for aggregation results conditional on sorted portfolios. Finally, we report the aggregate moments, the return spreads, and corporate ratios across portfolios from our model and compare them with our data.

5.4 Aggregate Moments

We first examine the quantitative performance of our model at the aggregate level and document our model's success in matching a wide set of conventional moments in macroeconomic quantities and asset prices. Most importantly, our model delivers a sizable asset durability spread at the aggregate level.

Table 5 reports the key moments of macroeconomic quantities (top panel) and those of asset returns (bottom panel), respectively, and compares them to their counterparts in the data when available. The top panel shows that the model simulated data are broadly consistent with the basic features of the aggregate macro-economy in terms of volatilities, correlations, and persistence of output, consumption, and investment. In sum, our model is as successful as neoclassical growth models in accounting for the dynamics of macroeconomic quantities.

[**Place Table 5 about here**]

With respect to the asset pricing moments (bottom panel), we make two observations. First, our model is reasonably successful in generating moments related to financial frictions and asset pricing at the aggregate level. In particular, it replicates a low and smooth risk-free rate, with a mean of 1.22% and a volatility of 0.48%. The equity premium and leverage ratio in this economy are 6.88% and 0.44, respectively, and broadly consistent with the empirical target of 5.71% and 0.31 in the data. Our model also delivers large levered and unlevered returns on acquiring durable capital (i.e., 10.79% and 6.14%.) Second, our model confirms that return differences between durable and non-durable capital investment are more pronounced when credit constraint is binding. This holds regardless of whether the durable capital spread is measured using levered returns or unlevered returns. Specifically, expected return differences between durable and non-durable capital investment are 7.05% (levered returns) and 3.16% (unlevered returns), respectively, when the collateral constraint is binding. Though we are unable to directly uncover empirical moments on returns at the asset level from the BEA table, our model later evaluates the asset durability spread against data as observed in the cross-section of stock portfolios.

5.5 Model Mechanisms

In this subsection, we numerically evaluate the performance of our quantitative model and further explore the model mechanisms that give rise to the asset durability premium.

First, we show that there is a risk-premium channel (i.e., equilibrium asset prices for more durable capital goods are more volatile over business cycles), which therefore commands a larger risk premium for holding such capital. Table 6 summarizes statistics that indicate that prices of more durable capital goods in our model economy are riskier. Specifically, we first simulate the aggregate time series and simply compute the average standard deviations of log capital prices of both types across model simulations. Our model generates more cyclical durable capital prices (with the standard deviation of 0.149), which are unconditionally more volatile compared to that of non-durable capital (with the standard deviation of 0.067). Next, we examine the source of this large price variability of durable capital by computing the covariance between the weighted stochastic discount factor $\widetilde{M}_{t+1}$ as in equation (28) and next period capital prices $q_{d,t+1}$ and $q_{nd,t+1}$ conditional on time t's information using simulated aggregate data. Our results in the third and fourth rows of the table suggest that durable capital prices are more negatively correlated with the stochastic discount factor (with the covariance of -0.059) as compared to that of the non-durable capital prices (with the covariance of -0.013). Since durable capital exhibits greater risk sensitivities to business cycles, a larger risk premium is associated with holding the durable capital. Finally, we compute the *elasticity* of log differences in capital prices with respect to changes in the liquidation probabilities in logs, by which financial shocks are the primary triggers for credit constraints to be binding. Our model results suggest that, on average, durable capital prices are more responsive to financial shocks (with the correlation of -0.933) compared to those of non-durable capital goods (with the correlation of -0.861). Therefore, across different measures, our model predicts that the price of durable capital can be as much as about three to four times more volatile than that of non-durable capital over business cycles, as measured by unconditional price volatility or by risk sensitivities driven by aggregate shocks. Hence, our quantitative model confirms the importance of our highlighted risk-premium channel in showing that durable capital is riskier in equilibrium.

[Place Table 6 about here]

Second, we evaluate firms' efforts to replace durable capital using non-durable capital when constraints are binding (i.e., substitution of asset durability.) Our first measure is the capital expense ratio on durable capital goods as a fraction of total capitalization, $Expense_t = \frac{q_{d,t}K_{d,t}}{q_{d,t}K_{d,t}+q_{nd,t}K_{nd,t}}$ with and without a binding constraint. Results from the top panel of Table 7 clearly suggest that firms' balance sheets shift toward more non-durable capital when constraints are binding, which amounts to a reduction of 2.81% of capital expense on durable capital moving from an unconstrained to a constrained situation. Our model solution accommodates a constant share of durable over non-durable ratio in quantities for $K_{d,t} = \zeta K_t$ and $K_{nd,t} = (1-\zeta)K_t$. Such drops in durable capital expense at the aggregate level are mainly reflective of the relative price changes in equilibrium. Our model clearly shows that the asset durability substitution between durable and non-durable capital is very consistent with greater price cyclicality of more durable capital on average, i.e., our highlighted risk-premium channel. Next, we examine only the quantity differences measured by the "excess investment" in durable capital relative to non-durable capital, i.e. $\frac{K_{d,t+1}-K_{nd,t+1}}{K_t} = \zeta\Gamma_t - (1-\zeta)\Gamma_t$, which factors out the impact of relative price changes and focuses on quantity substitution. Results from the bottom panel of Table 7 suggest that less capital investment goes to durable capital accumulation if firms are more financially constrained. This loss of investment in durable capital because of tightened constraints amounts to a 2.5% decrease from that under the unconstrained scenario. Therefore, we demonstrate that regardless of how we measure the asset durability substitution, either in nominal terms or real terms, aggregate shocks that bind credit constraints would trigger firms' asset holdings toward less expensive and less durable capital.

[Place Table 7 about here]

Next, we evaluate how important our risk-premium channel is to the point that durable capital investment commands a higher expected return in our model. Table 8 presents our model results when we fix capital prices to be constant over time. As we have shown in Subsection 4.2, the risk-premium channel is shut off if we do not allow for variation of capital prices over business cycles. In particular, we fix the capital prices at their respective steady-state values as they are in our baseline model by which $q_d^{ss} > q_{nd}^{ss}$. Hence, relative to our baseline model case, if acquiring durable capital now is not compensated for additional risk premium while durable capital is still more expensive for its larger down payment, then investing in durable capital investment is not an attractive option, for it fails to yield a higher expected return for entrepreneurs. Our counterfactual analysis suggests that expected return spreads between investing in durable relative to non-durable shrink and even turn negative on average when firms are unconstrained. When firms are more constrained, we show from equation (42) in Subsection 4.2 that the impacts of down payments and relative benefits between durable and non-durable capital are less pronounced; therefore, the expected return spread is somewhat less negative. In sum, the risk-premium channel is critically important for a general equilibrium analysis, both qualitatively and quantitatively, as it generates a large expected return spread for investing in durable capital relative to non-durable capital.

[Place Table 8 about here]

Finally, we compute the mean return spread reduction when financial constraint is binding, $\Omega_t = E[\theta\eta_t(\delta_{nd} - \delta_d)/E_t(\tilde{M})]$ as in equation (48), which measures the size of the capital collateralizeability effect that durable capital can be less risky as it provides extra collateral value. The collateralizability differences between type-d and type-nd capital goods, therefore, partially offset the model return spread commanded by acquiring more durable capital. The reduction of return spread matters only when constraints are binding $\eta_t > 0$. When we load our baseline calibration, as shown in Table 5, we find that this effect is small and reduces the return spread by about 22 basis points, which accounts for a tiny share of 7% (3%) of our total durable spread of 7.05% (3.16%) as measured in levered (unlevered) returns on financing durable capital investment when constraints are binding. Therefore, our quantitative model results suggest that the risk-premium channel dominates the offsetting collateralizeability channel, regardless of the effects driven by leverage ratios.

5.6 Impulse Response Functions

We further show that the impacts of our model mechanism on asset pricing can be best illustrated by looking into the model-implied impulse response functions of quantities and prices in response to exogenous aggregate shocks.

[Place Figure 1 about here]

In Figure 1, we plot the percentage deviations of quantities and prices from the steady state in response to one-standard-deviation of aggregate productivity shocks for shock period 1 (i.e., the shock to a.) over a 20-period horizon. In particular, since our model allows for collateral constraints to be binding only occasionally, the steady state of the shadow value of relaxing the borrowing constraint η_t has factored in both binding and non-binding periods. Three observations are summarized as follows. First, a positive shock to a (top panel in the left column) works as a negative discount rate shock to entrepreneurs, and the shock leads to a relaxation of the collateral constraint as reflected by a drop in the Lagrangian multiplier, η (top panel in the right column).

Second, relaxed collateral constraints translate into positive growth in the aggregate investment (second panel in the left column). Upon a positive productivity shock, not only does an entrepreneur's net worth jump sharply (third panel in the left column), but the price of type-d capital also increases sharply (second panel in the right column). However, the price of type-nd

capital rises with a smaller magnitude, in contrast to the price of type-d capital. This observation suggests that the price of durable capital presents higher risk sensitivities and greater price fluctuations driven by aggregate productivity shocks. The different risk profiles are also reflected in the different responses of the unlevered return on durable capital, r_d, and that on non-durable capital, r_{nd} when we factor impacts of leverage changes. The return of type-d capital responds much more to productivity shocks than that of type-nd capital (third panel in the right column). All these findings are consistent with our key model mechanism on asset durability substitution driven by a risk-premium channel.

Lastly and most importantly, we confirm the operation of asset durability substitution in economic expansions, when firms are collectively less constrained, they will prefer "more expensive" durable capital. We show the impulse response of durable capital expenditure as a fraction of total asset (i.e., Expense Ratio of $K_{d,t+1}$), reacting to a positive productivity shock (bottom panel in the left column). It shows that the aggregate acquisition of durable capital across all firms increases relative to share of non-durable capital expenditure. In addition, in terms of the quantities of investment in durable capital in excess of non-durable capital (bottom panel in the right column), we see more investment to support accumulating durable capital relative to non-durable capital when the economy sees positive aggregate productivity shocks. All these impulse responses reflect the key channel on asset durability substitution, which explains why the price and returns on type-d capital increase even more significantly, as shown in the second and third panel in the right column.

Next, we introduce one standard deviation positive shocks to raise the liquidation probability λ_t. We then present the impulse responses of these key variables of interest to such adverse financial shocks in Figure 2.

[Place Figure 2 about here]

First, a positive shock to x_t raises the likelihood of a firm being liquidated λ as of the shock period 1 shown in the figure (top panel in the left column). It then works as a positive discount rate shock to entrepreneurs, which leads to a tightening of the collateral constraint, and results in an increase in the Lagrangian multiplier, η (top panel in the right column.)

Second, tightened collateral constraints result in slumps both in investment (second panel in the left column) and in entrepreneurs' net worth (third panel in the left column). In addition, the price of type-d capital drops dramatically (second panel in the right column), although the price of type-nd capital tumbles only slightly. We also see drops in both the unlevered return on type-d capital, r_d, and that on type-nd capital, r_{nd}, although the former has relatively larger decreases (third panel in the right column). Overall, we see durable capital as a riskier asset than non-durable capital by exhibiting larger risk sensitivities in case of a bad financial shock.

Finally, impulse responses of the relative capital expenditure on durable capital and excess investments in durable capital accumulation again confirm capital substitutabilities effects with negative financial shocks. Intuitively, when firms are more constrained in recessions after a bad liquidation shock, they prefer acquiring "cheaper" non-durable capital. The economy starts spending more on non-durable capital relative to a share of the total capital (bottom panel in the left column). The capital accumulation using durable capital in excess of non-durable capital through investment also shrinks (bottom panel in the right column.) All these substitutions also rationalize the different risk profiles of durable and non-durable capital to financial shocks in addition to productivity shocks (the second and third panel in the right column).

In summary, our model-implied impulse response functions of key variables to both aggregate shocks all suggest that returns on type-d capital, r_d respond much stronger than that on type-nd capital, r_{nd}, to aggregate shocks by exhibiting larger risk sensitivities. Hence, durable capital is indeed much riskier than non-durable capital over business cycles driven by both types of shocks; therefore, holding durable capital necessarily commands for a greater expected return spread.

5.7 Asset Durability Spread

We now turn to the implications of our model on the cross-section of asset durability-sorted portfolios. We simulate firms from the model, measure the durability of firm assets, and conduct the same asset durability-based portfolio-sorting procedure as in the data.[23] In Table 9, we report the average returns of sorted portfolios, along with several other characteristics from the data and those from the simulated model.

[Place Table 9 about here]

Table 9 first reports several other characteristics of the asset durability-sorted portfolios that inform the economic mechanism we emphasize in our model. First, not surprisingly, the asset durability measure is monotonically increasing across asset durability-sorted portfolios.[24] In addition, our model-based portfolios with largest durability and lowest durability exhibit similar depreciation rates, 0.08 and 0.18, respectively, as correspondence to the depreciation rates of portfolios constructed in the data, 0.11 and 0.19, respectively. For each portfolio in between, the model-based depreciation rates are close enough to the data counterparts. This provides important validity of our model for studying the return spread across portfolios sorted by asset durability, even if we

[23] In our simulation, extremely financially constrained firms might seek negative type-d capital by selling expensive capital, so they may acquire less expensive type-nd capital. Such a scenario could result in a negative accumulated net worth. To align with our empirical analysis, we enforce a restriction that type-d, type-nd capital, and net worth must be strictly positive for firms in our simulation. We then conduct the univariate portfolio sorting exercise, consistent with our empirical approach.

[24] Following the construction of the asset durability measure in Section 2, we define the asset durability in our simulation as the weighted average of the reciprocal of the depreciation rate with respect to durable and non-durable capital:

$$\text{Asset Aurability} = \frac{K_d}{K_d + K_{nd}} \times \delta_d^{-1} + \frac{K_{nd}}{K_d + K_{nd}} \times \delta_{nd}^{-1}. \tag{50}$$

are not calibrating our model to target the degree of asset durability for each portfolio. Second, as in the data, leverage is increasing in asset durability. This implication of our model is consistent with the data and the broader corporate finance literature (e.g. Ai, Li, Li, and Schlag (2020a)). However, the dispersion in leverage ratios in our model is slightly larger than in the data. Third, as we show in equation (III.23) in the Internet Appendix, positive idiosyncratic productivity tends to increase firms' production and investment that bind their financial constraints. Lacking sufficient net worth to obtain durable assets leads them to prefer less costly, non-durable assets, which reduces their asset durability. We report this firm characteristic in the fourth rows on both panels.[25] Our model again captures well of this empirical fact that firms with larger asset durability are less productive firms.

We next examine the asset durability premium in our model. As in the data, our simulated firms with high asset durability have a significantly higher average return than those with low asset durability. Quantitatively, our model produces a levered and unlevered asset durability spread of 4.36% and 1.32%, respectively. We see that our model rationalizes about 63% (30%) of the return spread differences in the data of 6.93% in levered returns (4.75% in unlevered returns). Taking the average asset durability premium from the data, 5.01%, across the scenarios of using four different financial constraint measures, according to Panels A to D in Table 3. Our model thus accounts for more than 80% of the levered-return based spread in the data. Hence, regardless of measures, our model predicts a sizable and positive asset durability premium.

Given our highlighted model mechanism of asset durability substitution driven by aggregate shocks that tighten credit constraints over business cycles, our model produces sizeable asset durability premium quite well. The size of the premium is determined by the difference in the risk covariance as well as by cyclical properties of prices of durable and non-durable capital. In the cross-section, firms holding more durable capital are necessarily riskier for extra risk exposure and sensitivities; therefore, equity returns on these firms require extra risk compensations.

In addition, we emphasize that our model results shed light on the relationship between the tightness of firms' financial constraints and the expected stock returns. Our model mechanism features the fact that financially constrained firms may choose to acquire more non-durable capital on balance sheet as holding non-durable capital helps hedging against the aggregate uncertainty. These firms therefore appear to be less risky in equilibrium and command lower expected returns. Specifically, these constrained firms are not only less risky than those constrained firms who hold more durable capital, but also less risky as compared to those unconstrained firms with larger durable over non-durable capital ratio. Hence, our model insights may help ease the overly strong prediction of a positive relationship between financial constraints and the exposure to aggregate shocks as predicted by standard theories (e.g. Whited and Wu (2006), Buehlmaier and Whited (2018), and more recently Nikolov, Schmid, and Steri (2021)).

[25] Following Ai, Croce, and Li (2012), we estimate firm-level productivity from Compustat.

6 Empirical Analysis

In this section, we provide additional empirical evidence in supportive of our model mechanisms and predictions. We show that our findings confirm the interrelationships among firms' financial constraints, asset durability, and equity risk as predicted by our model. In particular, we examine the roles of financial frictions driven by aggregate uncertainty in shaping asset durability and stock returns across firms. Specifically, we construct a model-implied financial shock series and then examine its impacts on the cyclicality of capital prices and firms' substitution over asset durability. Based on a comprehensive list of asset pricing tests, we demonstrate that the asset durability premium is to compensate for firms' holdings of more durable capital with extra risk exposure.

6.1 Estimation of the Financial Shocks

Our model suggests that changes in the financial friction trigger compositional changes in firms' asset durability over business cycles, leading to the price cyclicality differences between durable and non-durable capital. Our empirical analysis aims to uncover from the data such mechanism by which shocks affecting the financial frictions are shifting the prices and quantities of asset durability changes. In our model, we study the shocks that affect the probability of liquidation of entrepreneurs by affecting their discount rates and their financing and capital decisions, i.e., financial shocks. Because the direct empirical correspondence of such liquidation shocks is not readily available in the data, our empirical strategy is to exploit the structure of our model to identify the financial shock proxy from the data.

Following Eisfeldt and Muir (2016) and Belo, Lin, and Yang (2018), we project the financial shocks within our model, through a multivariate linear regression, onto a set of moments. We then use the estimated regression coefficients along with the corresponding empirical moments at each date, to construct the fitted values of the projection and obtain our identified financial shocks, denoted as $\varepsilon_{x,t}^{\mathrm{Data}}$.[26]

We take two moments for the projection exercises – the changes in the aggregate debt-to-net-worth ratio, denoted by $\Delta\mathrm{BN}$, and the spread between the shadow interest rate and the risk-free rate, denoted by $R_I - R_f$ – and estimate the following regression using simulated data generated by our model

$$\varepsilon_{x,t} = \beta_1 \times \Delta\mathrm{BN}_t + \beta_2 \times (R_{I,t} - R_{f,t}) + u_t, \tag{51}$$

where $\Delta\mathrm{BN}_t$ and $R_{I,t} - R_{f,t}$ are normalized to have a mean of zero and a unit standard deviation. Our regression results suggest that these two moments account for most of the variation in the financial shocks within the model as determined by an average R^2 around 78%.

Specifically, we estimate equation (51) using simulated data for 100 times with each simulation

[26] The innovation to financial shocks, denoted as ε_x, is specified in Section 5.1. By the regression specification per equation (51), we obtain the fitted value of financial shocks as $\varepsilon_{x,t}^{\mathrm{Data}}$, which serves as the model-implied financial shocks.

path at a time. We then take the averaged estimated coefficients β_1 and β_2 across all simulation, obtaining the estimated slope coefficients $\beta_1 = 0.98$ and $\beta_2 = 0.09$. Intuitively, the positive slope coefficient on the change in the debt-to-net-worth ratio reflects that large liquidation shocks $\varepsilon_{x,t}$ are correlated with increased aggregate leverage. That is, an increase in liquidation probability leads to a decline in aggregate net worth, as shown in equation (9), and significantly tightens the borrowing constraints. This is because of firms are liquidated unexpectedly without production and the total income also drops given the negative correlations between financial shocks and productivity shocks. In addition, the positively estimated coefficient on $R_I - R_f$ suggests that tightened borrowing constraints also have a price impact on the cost of borrowing by increasing the credit spread.

Taking the two corresponding empirical moments related to the U.S. economy, we finally obtain a time series of annual frequency to proxy for the financial shocks covering years from 1960 to 2016. The empirical moment $\Delta \mathrm{BN}_t$ is constructed using the aggregate debt-to-equity ratio, while the spread $R_{I,t} - R_{f,t}$ is based on the default premium measured by the yield spread between Moody's Seasoned Baa and Aaa corporate bond yields, obtained from the Federal Reserve Economic Data (FRED).

We then plot the constructed model-implied financial shocks and the time series of the two empirical moments in the two panels of Figure 3. Across the panels, we see in the plots that our constructed financial shocks spiked while the debt-to-net-worth ratio and default risk premium also jumped during recessions. In addition, it is clear that financial innovations do not have to be always coupled with economic downturns as financial shocks can well increase outside the years of economic recession. For instance, sharp increases in $\varepsilon_{x,t}^{\mathrm{Data}}$ occur in 1978, 1985, and 1988, despite these years not being classified as recessions. Taking together, we find our model-implied financial shocks are generally counter-cyclical. Importantly, we note firms' financial conditions are not perfectly aligned with the business cycles, supporting our modeling approach in which aggregate uncertainty in our model are driven by both financial and productivity shocks and they are not perfectly correlated.

[Place Figure 3 about here]

6.2 Financial Frictions, Price Cyclicality, and Asset Durability

In this section, we investigate the impact of the model-implied financial shocks on our key model mechanism related to the risk-premium channel, echoing our theoretical results in Section 5.5. First, we present supporting evidence for firms' substitution over asset durability between durable and non-durable capital. Our model predicts that firms, especially those more financially constrained, prefer cheaper and less durable assets during recessions, as outlined in equation (III.23) in Section III of the Internet Appendix. To validate this prediction, we first calculate the cross-sectional averages of asset durability for the constrained and unconstrained firms each year, according to firms' dividend payment dummy (DIV). We then examine the reactions of asset durability to our model-implied financial shocks, by lagging the shock series by one year and controlling for other firm characteristics, per the following regression:

$$\text{Durability}_{t+1} = a + b \times \varepsilon_{x,t}^{\text{Data}} + c \times \text{Controls}_t + \varepsilon_t \tag{52}$$

As shown in Table 10, we present the estimation results of equation (52) for groups of financially constrained and unconstrained firms in Columns 1 and 2, respectively. The coefficient estimate b is 0.003 for the unconstrained firms group whereas the estimate is -0.16 for the constrained firms group, which is significantly negative as shown in Column 3. This finding conveys two key messages. First, it directly supports our primary model mechanism: the durability of financially constrained firms decreases with a positive realization of the financial shock, indicating a preference for cheaper, less durable assets when borrowing constraints are binding. This result aligns with our quantitative prediction in Table 7 of Section 5.5. Moreover, the slightly positive but insignificant coefficient in the unconstrained group suggests a capital reallocation channel: financially unconstrained firms, when facing negative financial shocks that reduce their holdings of durable capital, are also taking over liquidated durable capital from their constrained counterparts in general equilibrium. This offsetting channel therefore leads to small and insignificant coefficient estimate observed among the unconstrained group.

[**Place Table 10 about here**]

Next, as our model shows, financially constrained firms under adverse shocks shift their asset holdings towards cheaper and less durable assets, which leads to more cyclical prices of the durable capital goods relative to that of less durable capital goods in equilibrium. Consequently, these preferred less durable assets exhibit a lower degree of procyclicality in their pricing, rendering them less susceptible to aggregate risk driving financial frictions. In the following, we provide additional evidence and show that less durable assets indeed provide the insurance value against aggregate shocks.

We then take the log price differences for each asset in the Bureau of Economic Analysis (BEA) National Income and Product Accounts (NIPA) tables while classify the detailed assets into high- and low-durability groups according to their durability scores, as in Table 1 in Section 2.1. We finally construct the time series of capital price changes by averaging the price changes within each group.[27] We run the following regression for each asset durability group to estimate the risk sensitivity of its price changes with respect to financial frictions as proxied by the financial shock series in addition to the standard control of a market factor:

$$\Delta \text{Log } q_{h,t+1} = a_q + b_1 \times \text{MKT}_t + b_2 \times \varepsilon_{x,t}^{\text{Data}} + \varepsilon_{h,t},\ h \in \{H, L\}, \tag{53}$$

[27] For further insights into price indexes related to structures, equipment, and intellectual property products, we refer to NIPA Table 5.4.4, 5.5.4, and 5.6.4 (https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2).

where $\Delta \text{Log } q_{h,t+1}$ denotes the log price changes of a group of asset durability. MKT_t represents the market factor, and $\varepsilon^{\text{Data}}_{x,t}$ stands for the model-implied financial shocks.

We present the estimation results in Table 11. Column H finds a negative and statistically significant coefficient on the term of financial shocks associated with the high-asset-durability group. That is, shocks that tighten the financial constraints trigger larger price drops for assets having larger durability. By contrast, Column L suggests that the coefficient is indistinguishable from zero for the price changes related to assets in the low-asset-durability group. Financial constraints drive firms to hold less durable assets, which exacerbates shrinking demands for durable assets, which, in turn, results in a larger decline in the prices of durable assets. On the other hand, demands for less durable capital provide the buffer to the loss of asset values during economic downturns. Therefore, we establish the fact that assets with higher durability exhibit greater price sensitivities to aggregate shocks affecting financial frictions over business cycles.

[**Place Table 11 about here**]

Therefore, our empirical findings are perfectly consistent with our model prediction regarding the price cyclicality and the underlying risk premium channel, as demonstrated in Table 6, which shows that the price of durable capital is more correlated with the stochastic discount factor and exhibits greater price cyclicality. Consequently, more durable capital goods are substantially more exposed to shocks that affect the financial frictions than less durable capital goods. This generates profound asset pricing implications in the cross-section: firms of a portfolio comprising assets with higher durability are positioned as riskier entities and are expected to earn higher returns due to their extra risk exposure to financial frictions.

6.3 Cash Flow Sensitivities of Asset Durability-sorted Portfolios

We continue to provide additional evidence on the external validity of our model predictions. Our model delivers the asset durability premium in the cross-section of financially constrained firms because of the operating risk-premium channel that holding durable capital gives firms extra risk exposure to financial frictions over business cycles. Therefore, if non-durable capital provides the hedging value against aggregate uncertainty, we should see limited variations of cash flows that accrue to firms with low asset durability. In the following, we demonstrate at the portfolio level that firms with higher asset durability exhibit larger sensitivity in their cash flows with respect to the financial shocks both in the data and model.

In the data, we follow Belo, Li, Lin, and Zhao (2017) and compute portfolio-level normalized cash flow by aggregating EBIT within each quintile portfolio and normalizing it by lagged aggregate sales (SALE) of the respective portfolio. In the model, we aggregate profits within each quintile portfolio and normalize them by lagged aggregate total assets of the respective portfolio. This normalization process allows us to compute the sensitivity, or loading, of the cash flow concerning the two aggregate macroeconomic shocks under consideration.[28]

[Place Table 12 about here]

Table 12 presents the results on our estimated cash flow sensitivity to financial shocks both in data and in the model. In Panel A, empirically, the sensitivity of asset-durability-sorted portfolios follows a clear declining trend, ranging from 0.97 to -0.91 in response to the model-implied financial shocks $\varepsilon_{x,t}^{Data}$. The highest quintile portfolio exhibits a significantly lower loading than the lowest quintile, with a striking difference reflected in a t-statistic of -5.62. In contrast, the sensitivity to the market factor follows an insignificant zigzag pattern. In Panel B, based on model simulation, we find data-consistent results, showing a declining pattern in response to the financial shocks $\varepsilon_{x,t}$, with a t-statistic of -2.58, while the loadings on the productivity shock remain relatively flat. These findings provide additional angles to reaffirm the key mechanism in our model: assets with lower durability provide insurance against aggregate risk that determines the financial friction, unlike their higher-durability counterparts, which are more exposed to the risk.

6.4 Market Price and Exposure of Macroeconomic Shocks

In this section, we further explore a series of testable implications derived from our model. First, we apply the generalized method of moments (GMM) test to demonstrate that the model-implied financial shocks manifest a negative price of risk within the cross-section of asset-durability-sorted portfolios. This result is well aligned with the model prediction presented in Section 5.6. Second, we employ additional asset pricing tests using real and the simulated data from our model, and show that both the price of risk and the risk exposure of asset-durability-sorted portfolios exhibit a pattern consistent between data and our model.

Specifically, we examine the risk exposure of asset-durability-sorted portfolios to the model-implied financial shocks in the data. Our general equilibrium model accommodates the aggregate productivity and financial shocks as key sources of aggregate risk. Our empirical specification therefore outlines a two-factor framework wherein the first factor pertains to the market excess return, while the second factor is proxied by the model-implied financial shocks. This follows from Cochrane (2005) in order to evaluate the risk pricing of the financial shocks. In particular, we specify the stochastic discount factor (SDF) as follows:

$$\mathrm{SDF}_t = 1 - b_M \times \mathrm{MKT}_t - b_x \times \varepsilon_{x,t}^{\mathrm{Data}}, \tag{54}$$

This specification identifies the sources of risk that affect investors' marginal utility: MKT_t represents the market factor within the conventional capital asset pricing model (CAPM), while $\varepsilon_{x,t}^{\mathrm{Data}}$

[28]In untabulated results, we also explore alternative normalization measures (e.g., total assets, property, plant, and equipment) to compute sensitivity in relation to the financial shocks in the data. Remarkably, the result remains robust to the chosen normalization.

serves as our empirical proxy for the financial shocks. We are interested in the estimate of b_x, which measures the risk sensitivity to financial shocks.

To assess b_x, we employ the following set of test assets: our six asset-durability-sorted portfolios (as presented in Table 3), six size-momentum portfolios, and five industry portfolios.[29] Subsequently, we estimate the generalized method of moments (GMM) using the following set of moment conditions:[30]

$$\mathrm{E}[R_i^e] = -\mathrm{Cov}(\mathrm{SDF}_t, R_i^e), \tag{55}$$

which is the empirical equivalent to the Euler equation of our model, but with the conditional moments replaced by their unconditional counterparts. We essentially assess the ability of the financial shocks (i.e., $\varepsilon_{x,t}^{\mathrm{Data}}$) to price test assets based on residuals of the Euler equation.

Moreover, we adhere to practices in the literature, such as those outlined in Papanikolaou (2011), Eisfeldt and Papanikolaou (2013), and Kogan and Papanikolaou (2014), to compute two statistics that facilitate cross-sectional fitting. These statistics encompass the sum of squared errors (SSQE) and the mean absolute percent errors (MAPE). Additionally, we calculate the J-statistic for the overidentifying restrictions of our model. An insignificantly low J-statistic implies the non-rejection of the null hypothesis of zero pricing errors.

In Panel A of Table 13, we tabulate the estimation results of the fitted CAPM (Specification 1) and our two-factor SDF model (Specification 2). In Specification 1, we isolate the price of risk of the market factor, which is notably significant. After we incorporate the market factor with the financial shocks in Specification 2 as our reference, we observe that the price of the financial shocks is negative -0.53 and statistically significant at the 1% level.

To assess the asset pricing errors, the CAPM results exhibit SSQE and MAPE values of 5.70% and 5.13%, respectively. Upon the introduction of the financial shocks as the second source of risk to our model in Specification 2, these figures decrease to 5.64% and 5.11%, respectively. Despite the statistically insignificant outcome of the J-test in the CAPM model, we find that including the financial shocks effectively enhances model fitness by reducing the pricing errors. Notably, the JT difference test reveals statistical significance between the CAPM model and our two-factor model in Specifications 2.

To make sure that our empirical evidence is further aligned with our model, we conduct a similar GMM test using simulated data from our model with a two-factor specification: the first factor is denoted by the aggregate productivity shocks ε_a, and the second is the financial shocks ε_x.[31] As shown in Specification 3 of Panel A, the productivity shock carries a positive price of risk, while the financial shock exhibits a negative price of risk. Both estimates are statistically significant at the 5% significance level or better. Taken together, we show that the inclusion of the financial shocks

[29] This selection of test assets is in line with Belo et al. (2017) and Lin, Palazzo, and Yang (2020).

[30] For detailed insights into moment conditions, please refer to Table 13.

[31] We employ the following set of test assets simulated from our model: six asset-durability-sorted portfolios, five book-to-market-sorted portfolios, and five leverage-sorted portfolios.

in the stochastic discount factor enhances the performance of the CAPM model in pricing of stock returns. The empirical evidence on the price of risk is further validated by our model simulations.

[Place Table 13 about here]

In addition to the price-of-risk, in the upper panel of Panels B of Table 13, we show the estimated risk exposure (beta) of asset-durability-sorted portfolios (GMM-implied betas) to two factors along with the GMM-implied alphas in the data. Our findings show that the exposure to the market factor (β^i_{MKT}) display uniformity across asset-durability-sorted portfolios.[32] However, more importantly, we find that the risk exposure to model-implied financial shocks exhibits a clear and significant descending trend from the low-asset-durability portfolio to the high-asset-durability portfolio. This pattern showcases an increasing risk covariance with the negatively priced financial shocks as the asset durability increases at the portfolio-level in the data.

Similarly, we provide estimations of risk exposures to aggregate productivity shocks and financial shocks based on simulation data from our model. The results are summarized in the lower panel of Panel B. Clearly, we find an upward-sloping trend in risk exposure to productivity shocks but a downward-sloping trend in exposure to financial shocks from the low-asset-durability portfolio to the high-asset-durability portfolio. While the simulation results accord well with findings in the data, we demonstrate both in the data and in the model that asset durability exhibits an increasing covariance with the positively priced productivity shocks and the negatively priced financial shocks.

In summary, we document additional and important evidence confirming that the asset durability premium in the cross-section of financially constrained firms is a result of the risk-premium channel as we highlighted in our model. High-asset-durability firms earn higher expected stock returns by exhibiting more negative betas on financial shocks, a factor that is negatively priced. Furthermore, incorporating the financial shocks reduces the pricing errors of portfolios associated with varied asset durability.

6.5 Additional Empirical Asset Pricing Tests

Finally, we provide additional evidence to establish the robustness of our results using alternative measures and rule out other explanations that may potentially drive the results on asset pricing related to the asset durability.

First, instead of using our model-implied financial shocks for the asset pricing tests, we take alternative measures of financial shocks for estimating the 2-factor model using GMM and for estimating the risk-exposure (beta) to the two sources of aggregate risk along the asset durability-sorted portfolios. In Table IA.1 of Internet Appendix, we summarize the estimation results using the default premium and the GZ spread (Gilchrist and Zakrajšek, 2012) to denote the financial shocks

[32] We modify the code of Kan, Robotti, and Shanken (2013) to calculate test assets' alphas and t-statistics based on Chapter 12 of Cochrane (2005).

individually. We again confirm the robustness of our results that financial shocks are negatively priced and the high-durability portfolio is more negatively exposed to the financial shocks.

Second, we examine the degree to which the variability in asset durability for return predictability can be accounted for by conventional risk factors or certain firm characteristics. We execute an array of asset pricing factor assessments and report the results in Table IA.2 in our Internet Appendix. We find that the observed positive relationship between asset durability and returns remains largely unaltered even if we include other systematic risks and firm characteristics. Our findings underscore that the dispersion of returns across portfolios sorted on asset durability cannot be explained by risk exposures to other risk factors. Notably, the alphas in the long-short portfolio retain their statistical significance.

Third, to further explore the asset-durability-return relationship, we employ Fama and MacBeth (1973) regressions as outlined in Section I.1.3 of our Internet Appendix. We do so to rule out potential alternative explanations. The outcomes of these Fama-Macbeth regressions closely mirror our previous findings, particularly when we arrange portfolios based on asset durability. As shown in Table IA.3, the asset durability continues to significantly and positively predict future stock returns. Most notably, this predictability remains robust even in the presence of established predictors for stock returns that are found in the literature, e.g., firms' leverage and the collateralizeability value of assets.

7 Conclusion

Durable capital is more expensive to finance not only for its greater down payment but also for its larger price risk sensitivities to financial frictions. We highlight a general equilibrium price effect that has critically important asset pricing implications for understanding firms' equity risk due to asset durability, especially when financial constraints matter. With a novel metric to gauge asset durability based on firms' assets, we document a substantial return differential of 5% annually between firms with high asset durability and those with low asset durability when firms are financially constrained. Considering firms' dynamic capital choices between choosing durable and non-durable capital, we develop a general equilibrium asset pricing model incorporating heterogeneous firms and occasionally binding collateral constraints. Tightened financial constraints trigger firms to opt for reduced position in holding durable capital, which helps alleviate collateral constraints under adverse aggregate shocks. Our model then uncovers the risk-premium channel that durable asset prices exhibit greater cyclicality and larger risk exposure to aggregate risk. In the cross-section, firms with larger asset durability are therefore more exposed to financial frictions driven by aggregate uncertainty and earn higher expected returns. Our model is able to generate sizeable differential risk exposure across portfolios of asset durability, which helps rationalize the asset durability premium in the cross-section.

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Figure 1. Impulse Responses to 1 S.D. Productivity Shock

This figure plots the log-deviations from the steady state for quantities and prices associated with a one-standard-deviation positive shock to a_t in period 1. One period is a year. All parameters are calibrated as in Table 4.

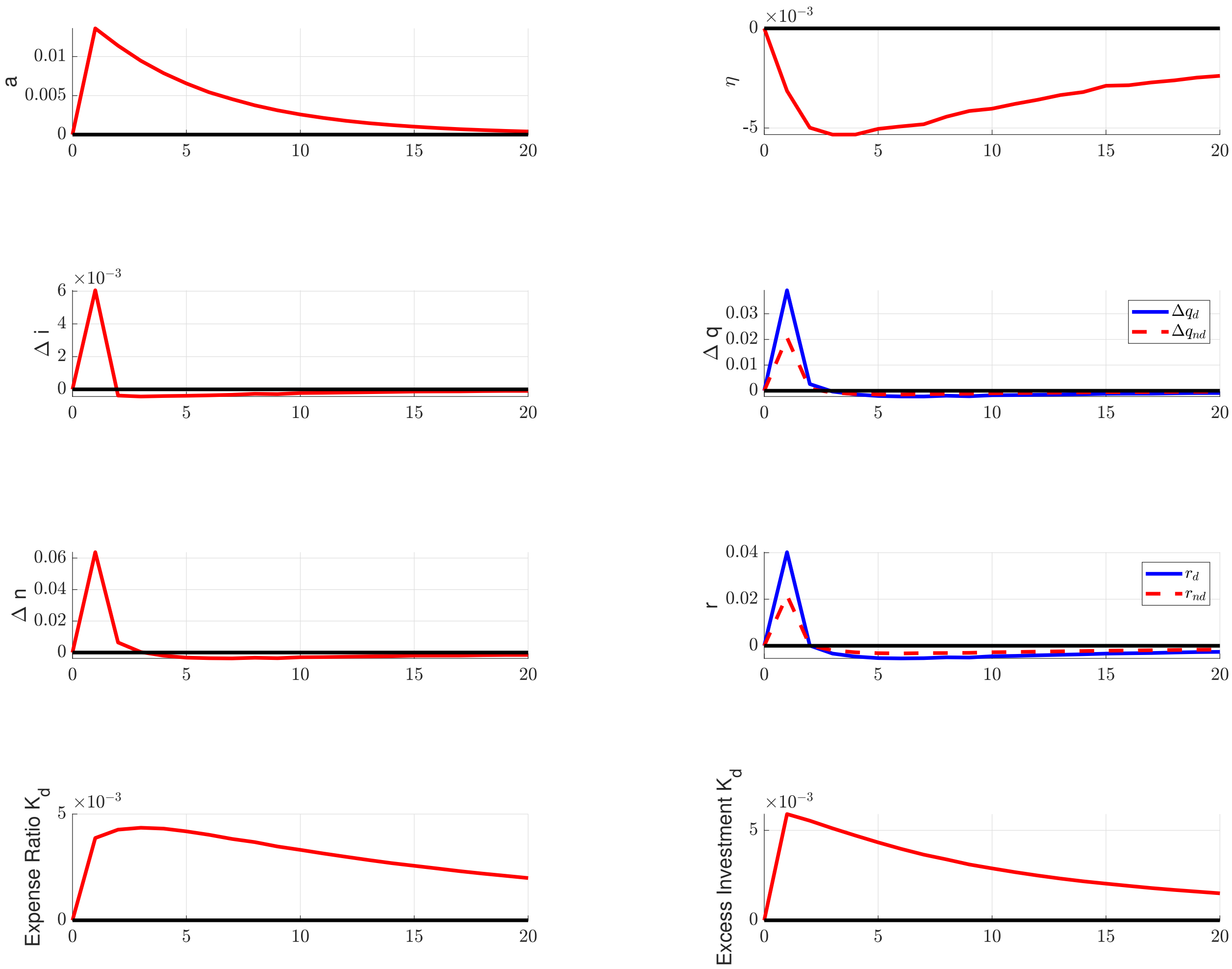

Figure 2. Impulse Responses to 1 S.D. Liquidation Shock

This figure plots the log-deviations from the steady state for quantities and prices associated with a one-standard-deviation positive shock to x_t in period 1. One period is a year. All parameters are calibrated as in Table 4.

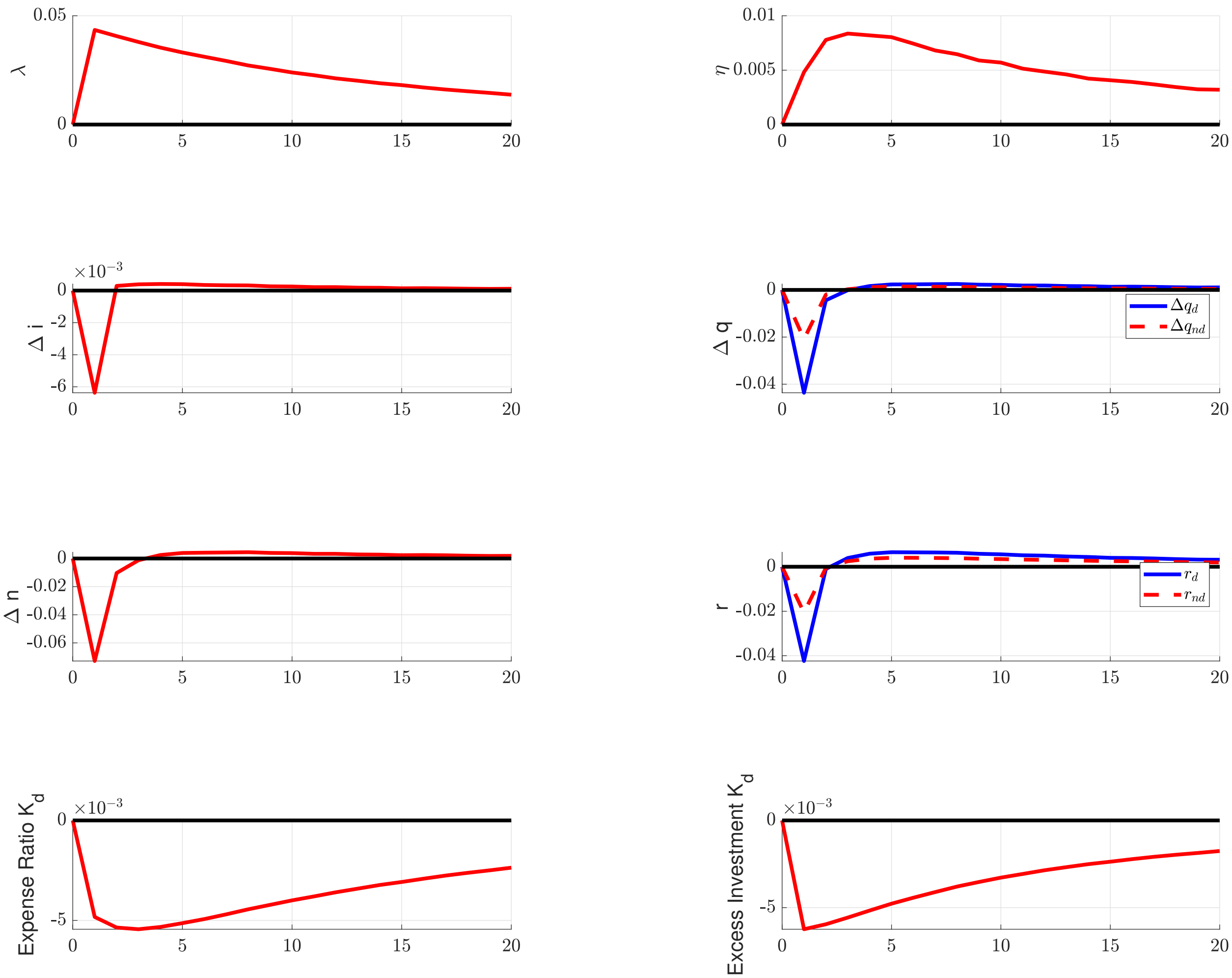

Figure 3. Model-implied Financial Shocks

This figure reports the time series of the model-implied financial shocks (top panel) and the time series of the change in the debt-to-net-worth ratio and the default premium (bottom panel). Shaded bars represent NBER recession years. Data are annual from 1960 to 2016.

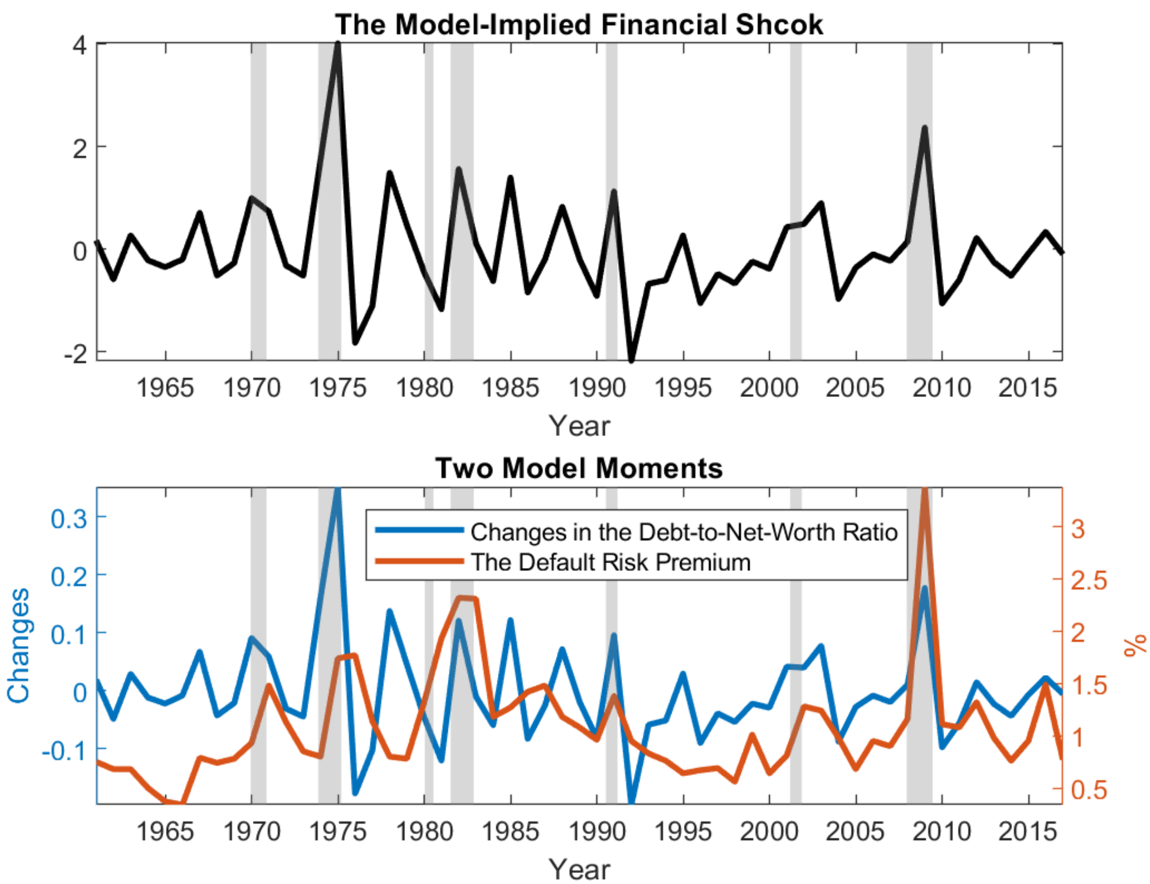

Table 1: Durability and Financial Constraints

This presents our regression coefficients of asset durability on different financial constraints, while also controlling for the firm fixed effect. We provide definitions of variables in Table IA.6. All independent variables possess a mean of zero and a standard deviation of one, following winsorization at the 1st and 99th percentiles of their empirical distribution. Our reported t-statistics in parentheses are based on standard errors clustered at the firm level. Our sample omits utility, financial, public administrative, and public administrative industries, and covers the period from 1977 to 2016.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Non-DIV	-0.10				-0.10		
[t]	-1.92				-1.91		
SA		-1.41				-1.34	
[t]		-14.28				-13.20	
WW			-0.32				-0.38
[t]			-4.23				-5.52
ROA				0.14	0.31	0.24	0.30
[t]				6.57	14.14	10.81	12.92
Log ME					-0.02	-0.52	-0.31
[t]					-0.34	-8.15	-5.08
Log B/M					0.14	-0.07	-0.01
[t]					5.36	-2.48	-0.59
I/K					-0.22	-0.23	-0.17
[t]					-12.28	-12.58	-9.05
Book Lev.					0.31	-0.39	-0.14
[t]					1.88	-2.40	-0.84
Cash/AT					0.43	0.44	0.45
[t]					13.98	14.12	14.29
Redp					0.04	0.02	0.02
[t]					0.24	0.17	0.13
TANT					3.01	3.00	2.93
[t]					38.07	38.38	36.06
Observations	133,830	133,830	123,654	133,685	99,292	99,292	94,299
R-squared	0.87	0.88	0.88	0.87	0.91	0.91	0.92
Controls	No	No	No	No	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2: Summary Statistics

This table provides a comprehensive overview of summary statistics pertaining to both the main outcome variables and control variables within our sample. The precise definitions of asset durability and depreciation measures are outlined in Section 2.1. Panel A dissects the entire sample into constrained and unconstrained firms based on a dividend payment dummy (DIV), as classified by Farre-Mensa and Ljungqvist (2016), at the end of each June. We show the pooled means of these variables, weighted by firm market capitalization at fiscal year-end. Panel B showcases time-series averages representing the cross-sectional median of firm characteristics within constrained firms. These firms are segmented into five portfolios based on their asset durability relative to industry peers. We use NAICS 3-digit industry classifications to carry out our categorizations. Further definitions of our variables can be found in Table IA.6 of the Internet Appendix. Our sample spans the period from 1977 to 2016, and excludes financial, utility, and public administrative sectors.

	Panel A: Pooled Statistics		**Panel B: Firm Characteristics**				
	Const.	**Unconst.**	**Portfolios**				
Variables	**Mean**		**L**	**2**	**3**	**4**	**H**
Durability	12.66	16.54	7.69	9.99	11.45	14.24	18.00
Depreciation	0.17	0.13	0.19	0.16	0.15	0.13	0.11
Book Lev.	0.24	0.33	0.13	0.19	0.21	0.28	0.32

Table 3: Portfolios Sorted on Asset Durability

This table shows average excess returns for five portfolios sorted on asset durability across firms relative to their industry peers. To obtain these results, we use NAICS 3-digit industry classifications and rebalance portfolios at the end of every June. Our results reflect monthly data from July 1978 to December 2017 and exclude utility, financial, public administrative, and public administrative industries. We split the whole sample into financially constrained and unconstrained subsamples at the end of every June, as classified by dividend payment dummy, SA index, a rating dummy, and a WW index. We report average levered and unlevered excess returns over the risk-free rate E[R]-R_f, standard deviations Std, as well as report Sharpe ratios SR across five portfolios in constrained subsamples (Panel A) and in the whole sample (Panel B). We estimate standard errors by using the Newey-West correction. We also include t-statistics in parentheses and annualize portfolio returns by multiplying by 12. All returns, standard deviations, and Sharpe ratios have been annualized.

	Levered Returns						**Unlevered Returns**					
	Panel A: Constrained Subsample											
	L	**2**	**3**	**4**	**H**	**H-L**	**L**	**2**	**3**	**4**	**H**	**H-L**
	DIV											
E[R]-R_f (%)	5.39	9.57	9.34	9.03	12.32	6.93	3.73	6.91	6.84	6.90	8.93	5.20
[t]	1.48	2.81	2.81	2.92	3.62	2.86	1.32	2.52	2.77	2.86	3.57	3.17
Std (%)	26.79	25.32	24.81	24.05	24.09	11.8	20.25	19.84	18.79	18.60	17.34	9.22
SR	0.20	0.38	0.38	0.38	0.51	0.59	0.18	0.35	0.36	0.37	0.51	0.56
	SA											
E[R]-R_f (%)	4.53	7.59	7.97	8.39	9.63	5.10	2.94	5.81	5.40	5.60	6.62	3.68
[t]	1.12	1.89	1.98	2.35	2.77	2.54	1.07	2.75	2.54	3.19	4.05	2.13
Std (%)	24.45	23.55	24.34	21.09	20.70	11.58	18.77	18.07	18.57	14.7	14.33	9.97
SR	0.19	0.32	0.33	0.40	0.47	0.44	0.16	0.32	0.29	0.38	0.46	0.37
	Rating											
E[R]-R_f (%)	5.65	8.76	9.40	9.35	10.10	4.45	4.15	6.92	7.64	7.54	7.96	3.81
[t]	1.42	2.18	3.06	2.84	3.52	2.12	1.42	2.60	3.62	3.77	4.37	2.13
Std (%)	24.32	23.4	19.61	19.89	18.81	11.80	19.92	19.93	16.10	16.32	15.23	9.98
SR	0.23	0.37	0.48	0.47	0.54	0.38	0.21	0.35	0.47	0.46	0.52	0.38
	WW											
E[R]-R_f (%)	6.09	8.24	9.13	9.59	9.65	3.56	4.42	6.55	7.01	7.00	6.85	2.42
[t]	2.13	2.78	3.68	3.78	3.85	2.23	1.99	2.78	3.40	3.74	3.67	1.76
Std (%)	25.70	24.18	23.67	21.10	20.85	11.04	20.07	18.96	18.71	15.23	14.92	9.66
SR	0.24	0.34	0.39	0.45	0.46	0.32	0.22	0.35	0.37	0.46	0.46	0.25
	Panel B: Whole Sample											
E[R]-R_f (%)	7.36	8.10	8.12	8.65	8.79	1.44	4.85	5.30	5.82	5.60	5.75	0.90
[t]	2.70	3.49	3.26	4.17	3.55	1.03	2.6	3.29	3.58	3.65	3.62	0.98
Std (%)	19.25	16.75	15.14	15.15	17.37	8.72	12.96	11.4	10.53	10.77	11.4	5.94
SR	0.38	0.48	0.54	0.57	0.51	0.17	0.37	0.46	0.55	0.52	0.50	0.15

Table 4: Calibration

This table reports parameter values we used for our model calibrated to data of annual frequency.

Parameter	**Symbol**	**Value**
Relative risk aversion	γ	10
IES	ψ	2
Capital share	α	0.32
Span of control parameter	ν	0.85
Time discount factor	β	0.984
Death rate of entrepreneurs	$E(\lambda)$	0.12
Inv. adj. cost parameter	τ	7
Mean productivity growth rate	$E(\tilde{A})$	0.599
Durable capital dep. rate	δ_d	0.05
Non-durable capital dep. rate	δ_{nd}	0.19
Mean fraction of durable capital over total asset	ζ	0.645
Collateralizability parameter	θ	0.511
Entering entrepreneurs' net worth over capital ratio via transfers	χ	0.35
Persistence of TFP shocks	ρ_A	0.83
Persistence of liquidation shocks	ρ_x	0.95
S.D. of TFP shocks	σ_A	0.027
S.D. of liquidation shocks	σ_x	0.186
Shock correlation coefficient	$\rho_{A,x}$	-0.85
Mean idio. productivity growth	μ_ϵ	0.005
S.D. of idio. productivity growth	σ_ϵ	0.14

Table 5: Model Simulations and Aggregate Moments

This table presents annualized moments from our model simulations and the data whenever available. The model moments are calculated based on repetitions of sample simulations. We carry out our simulation at an annual frequency. Our reported moments pertain to these annual observations. The market return (R_M) reflects the return on entrepreneurs' net worth, incorporating endogenous financial leverage. R_h^{Lev} and R_h represent the returns on maximally levered and non-levered capital for capital type $h \in \{d, nd\}$, respectively, which we compute based on average financial leverage in the economy. Volatility, correlations, and first-order autocorrelation are denoted as $\sigma(.)$, $corr(.,.)$ and $AC1(.)$, respectively. The average reduction in return spread driven by the collateralizeability channel is denoted by $\Omega_t = E[\theta\eta_t(\delta_{nd} - \delta_d)/E_t(\tilde{M})]$ defined in equation (48). "Constrained" and "Unconstrained" refer to model moments computed using the subsamples of our simulation when the shadow value of borrowing constraint $\eta_t > 0$ and $\eta_t = 0$, respectively. Returns and return spreads are all expressed in percent (%).

Moments	**Data**	**Model**
$\sigma(\Delta y)$	3.05	2.96
$\sigma(\Delta c)$	2.53	2.46
$\sigma(\Delta i)$	10.30	6.45
$corr(\Delta c, \Delta i)$	0.39	0.6
$AC1(\Delta c)$	0.49	0.27
Leverage ratio	0.31	0.44
$E[R_M - R_f]$	5.71	6.88
$\sigma(R_M - R_f)$	20.89	8.29
$E[R_f]$	1.2	1.22
$\sigma(R_f)$	0.97	0.48
$E[R_d^{Lev}]$		10.79
$E[R_d^{Lev} - R_{nd}^{Lev}]$		5.24
$E[R_d^{Lev} - R_{nd}^{Lev}]$ (Constrained)		7.05
$E[R_d^{Lev} - R_{nd}^{Lev}]$ (Unconstrained)		2.71
$E[R_d]$		6.14
$E[R_d - R_{nd}]$		2.39
$E[R_d - R_{nd}]$ (Constrained)		3.16
$E[R_d - R_{nd}]$ (Unconstrained)		1.33
Ω_t		0.22
$\frac{\Omega_t}{E[R_d^{Lev} - R_{nd}^{Lev}]}$ (Constrained)		0.070
$\frac{\Omega_t}{E[R_d - R_{nd}]}$ (Constrained)		0.031

Table 6: Cyclicality of Equilibrium Capital Prices

This table presents model-implied moments measuring the unconditional and conditional variability of capital prices of both capital types. The model moments are calculated based on repetitions of sample simulations of annual frequency. Volatility, covariance, and correlation coefficient are denoted as $\sigma(.)$, $cov(.,.)$ and $corr(.,.)$, respectively. For each type of capital $h \in \{d, nd\}$, $log[q_{h,t}]$ denotes capital prices in natural logarithm. $\widetilde{M}_{t+1}$ is the augmented stochastic discount factor as defined in equation (28). λ_t denotes the probability of a firm being liquidated in period t.

Moments	**Model**
$\sigma(\log[q_{d,t}])$	0.149
$\sigma(\log[q_{nd,t}])$	0.067
$cov(q_{d,t+1}, \widetilde{M}_{t+1})$	-0.059
$cov(q_{nd,t+1}, \widetilde{M}_{t+1})$	-0.013
$corr(\Delta \log[\lambda_t], \Delta \log[q_{d,t}])$	-0.933
$corr(\Delta \log[\lambda_t], \Delta \log[q_{nd,t}])$	-0.861

Table 7: Substitution of Durable vs. Non-durable Capital

This table presents model-implied moments measuring the degree of firms' capital substitution between asset durability concerning the tightness of borrowing constraints. The model moments are calculated based on repetitions of sample simulations of annual frequency. $E(\frac{q_{d,t}K_{d,t}}{q_{d,t}K_{d,t}+q_{nd,t}K_{nd,t}})$ denotes the average "expense ratio" which measures firm's relative capital expense on durable capital over total asset. $E(\frac{K_{d,t+1}-K_{nd,t+1}}{K_t})$ denotes the average "excess investment" in capital accumulation of durable relative to non-durable capital. "Constrained" and "Unconstrained" refer to model moments computed using the subsamples of our simulation when the shadow value of borrowing constraint $\eta_t > 0$ and $\eta_t = 0$, respectively. Relative change refers to the average drop of "expense ratio" and "excess investment" in durable capital when firms are constrained as compared to those under unconstrained time in relative terms and in percent.

Moments	**Model**
$E(\frac{q_{d,t}K_{d,t}}{q_{d,t}K_{d,t}+q_{nd,t}K_{nd,t}})$	0.791
$E(\frac{q_{d,t}K_{d,t}}{q_{d,t}K_{d,t}+q_{nd,t}K_{nd,t}})$ *(Constrained)*	0.782
$E(\frac{q_{d,t}K_{d,t}}{q_{d,t}K_{d,t}+q_{nd,t}K_{nd,t}})$ *(Unconstrained)*	0.804
Relative Change	-2.81%
$E(\frac{K_{d,t+1}-K_{nd,t+1}}{K_t})$	0.297
$E(\frac{K_{d,t+1}-K_{nd,t+1}}{K_t})$ *(Constrained)*	0.294
$E(\frac{K_{d,t+1}-K_{nd,t+1}}{K_t})$ *(Unconstrained)*	0.302
Relative Change	-2.50%

Table 8: Additional Model Results: Fixed Capital Prices

This table presents annualized moments from the model simulations for returns on capital investment. The model moments are calculated based on repetitions of sample simulations. We carry out our simulation at an annual frequency. We fix capital prices to be constant over time and at their respective steady state values as they are in our baseline model by which $q_d^{ss} > q_{nd}^{ss}$ when financial constraints are imposed. R_h^{Lev} and R_h represent the returns on maximally levered and non-levered capital for capital type $h \in \{d, nd\}$, respectively. "Constrained" and "Unconstrained" refer to model moments computed using the subsamples of our simulation when the shadow value of borrowing constraint $\eta_t > 0$ and $\eta_t = 0$, respectively.

Moments	**Model**
$E[R_d^{Lev}]$	8
$E[R_d^{Lev} - R_{nd}^{Lev}]$	-0.3
$E[R_d^{Lev} - R_{nd}^{Lev}]$ (Constrained)	-0.28
$E[R_d^{Lev} - R_{nd}^{Lev}]$ (Unconstrained)	-0.48
$E[R_d]$	5.38
$E[R_d - R_{nd}]$	-0.56
$E[R_d - R_{nd}]$ (Constrained)	-0.54
$E[R_d - R_{nd}]$ (Unconstrained)	-0.76

Table 9: Asset Durability Spread, Data, and Model Comparison

This table provides a comparison of moments between empirical data (Panel A) and model-simulated data (Panel B) at the portfolio level. Panel A presents statistics computed from the subset of financially constrained firms in the data, categorized by the dividend payment dummy (DIV). In Panel B, we conduct a model simulation and replicate the same portfolio sorting that we conducted with our empirical data. Both Panel A and Panel B present the time-series average of cross-sectional median firm characteristics, utilizing year-end values. These characteristics include asset durability, depreciation rate, book leverage, idiosyncratic productivity, and levered and unlevered return on equity. Additionally, we report excess returns E[R]-R_f(%) (annualized by multiplying by 12, in percentage terms) for quintile portfolios sorted based on asset durability.

	L	**2**	**3**	**4**	**H**	**H-L**
			Panel A: Data			
Asset Durability	7.69	9.99	11.45	14.24	18.00	
Depreciation	0.19	0.16	0.15	0.13	0.11	
Book Lev.	0.13	0.19	0.21	0.28	0.32	
Idio. Productivity	1.04	1.02	1.00	0.96	0.85	
E[R]-R_f (%)	5.39	9.57	9.34	9.03	12.32	6.93
E[R]-R_f Unlevered (%)	4.09	7.43	6.77	7.29	8.84	4.75
			Panel B: Model			
Asset Durability	6.14	7.57	9.32	12.02	16.72	
Depreciation	0.18	0.17	0.15	0.13	0.08	
Book Lev.	0.22	0.25	0.28	0.33	0.41	
Idio. Productivity	1.03	1.02	1.01	0.99	0.97	
E[R]-R_f (%)	7.22	7.99	8.77	9.88	11.57	4.36
E[R]-R_f Unlevered (%)	5.42	5.83	6.17	6.53	6.74	1.32

Table 10: The Effect of Financial Shocks on Quantity Dynamics

This table presents the sensitivity of asset durability in year $t+1$ to the model-implied financial shocks $\varepsilon_x^{\text{Data}}$. We first calculate the cross-sectional average asset durability for both constrained and unconstrained firms each year, using the dividend payment dummy (DIV). We then examine the sensitivity of asset durability to the model-implied financial shocks, along with other firm characteristics, by reporting the estimated coefficients on asset durability. Standard errors are calculated using the Newey-West correction. All independent variables are standardized to have a mean of zero and a standard deviation of one.

	Const.	**Unconst.**	**Const.-Unconst.**
$\varepsilon_x^{\text{Data}}$	-0.16	0.00	-0.06
[t]	-2.11	0.24	-2.09
Log ME	-1.38	-1.75	-0.04
[t]	-13.75	-14.60	-0.55
Log B/M	0.18	-0.23	0.26
[t]	2.49	-2.24	5.54
I/K	-0.08	-0.04	0.02
[t]	-1.18	-0.58	1.55
ROA	0.00	-0.15	0.11
[t]	0.01	-1.70	2.07

Table 11: The Effect of Financial Shocks on Price Dynamics

This table shows the exposure of price dynamics to the model-implied financial shocks. We classify detailed assets into high- and low-durability groups based on their durability scores. Next, we compute the price changes for each asset and average them within each group across years to construct the time series of price changes. All estimates are based on the following time-series regressions:

$$\Delta \text{Log } q_{h,t+1} = a_q + b_1 \times \text{MKT}_t + b_2 \times \varepsilon_{x,t}^{\text{Data}} + \varepsilon_{h,t},\ h \in \{H, L\},$$

in which ΔLog $q_{h,t+1}$ represents the log difference of price changes in the high H and low L asset durability groups. MKT_t represents the market factor, and $\varepsilon_{x,t}^{\text{Data}}$ stands for the model-implied financial shocks. To ensure robustness, we calculate standard errors using the Newey-West correction method. Corresponding t-statistics are reported within parentheses.

	L	**H**
MKT	-0.48	-0.05
[t]	-0.59	-0.17
$\varepsilon_x^{\text{Data}}$	0.12	-0.74
[t]	0.21	-2.68
Observations	40	40
R-square	0.07	0.27

Table 12: Cash Flow Sensitivity

This table presents the cash flow sensitivity of asset-durability-sorted portfolios to financial shocks. In the data, we compute portfolio-level normalized cash flow by aggregating EBIT within each quintile portfolio and normalizing it by lagged aggregate sales (SALE) of the respective portfolio. In the model, we aggregate profits (Π) within each quintile portfolio and normalize them by lagged aggregate total assets ($q_d K_d + q_{nd} K_{nd}$) of the respective portfolio. The regressions examine the sensitivity of normalized cash flows to financial shocks. In Panel A, we regress on the market factor (MKT) and the model-implied financial shock in the data, denoted as $\varepsilon_x^{\text{Data}}$. In Panel B, we use productivity and financial shocks from the model, represented as ε_a and ε_x, respectively. Reported coefficients are accompanied by standard errors computed using the Newey-West correction, with corresponding t-statistics in parentheses. All regressions are conducted at an annual frequency.

	L	**2**	**3**	**4**	**H**	**H-L**
Panel A: Data (MKT + $\varepsilon_{\mathbf{x}}^{\mathbf{Data}}$)						
MKT	0.88	0.31	0.46	-0.00	-0.08	-0.96
[t]	1.37	0.55	0.92	-0.02	-0.30	-1.50
$\varepsilon_x^{\text{Data}}$	0.97	-0.58	-0.60	-0.51	-0.91	-1.88
[t]	2.51	-1.02	-1.12	-1.84	-3.96	-5.62
Panel B: Model ($\varepsilon_{\mathbf{a}} + \varepsilon_{\mathbf{x}}$)						
ε_a	-0.006	-0.005	-0.003	-0.010	-0.008	-0.002
[t]	-0.395	-0.239	0.006	-0.667	-0.618	-0.324
ε_x	-0.003	-0.005	-0.007	-0.010	-0.010	-0.007
[t]	-0.732	-1.158	-1.544	-2.060	-2.341	-2.582

Table 13: Estimating the Market Price of Risk

In Panel A, we present the GMM estimates of the parameters of the stochastic discount factor (SDF), given by $SDF = 1 - b_M \times \text{MKT} - b_x \times \varepsilon_x^{\text{Data}}$ ($SDF = 1 - b_a \times \varepsilon_a - b_x \times \varepsilon_x$), using quintile portfolios sorted by asset durability. $\varepsilon_x^{\text{Data}}$ represents the model-implied financial shock in the data, while ε_a and ε_x correspond to productivity and financial shocks in the model. We normalize the SDF such that $E[SDF] = 1$, following Cochrane (2005). We report t-statistics and standard errors computed using the Newey-West procedure with three lags. To assess model fit, we include the sum of squared errors (SSQE), mean absolute pricing errors (MAPE), and the J-statistic for the overidentifying restrictions. Given the Euler equation $\text{E}[\text{SDF} \times R_i^e] = 0$, SSQE and MAPE are computed based on each testing asset i's moment error $u_i = \frac{1}{T}\sum_{t=1}^{T}\left[\widehat{\text{SDF}} \times R_{i,t}^e\right]$. SSQE and MAPE are defined as $\sum_{i=1}^{N} u_i \times u_i$ and $\frac{1}{N}\sum_{i=1}^{N}|u_i|$, in which N denotes the number of testing assets. In Panel B, we present the GMM-implied risk exposure of the testing portfolios: (β^i_{MKT} and $\beta^i_{x,\text{Data}}$) to the market factor and the model-implied financial shocks in the upper panel, as well as (β^i_a and β^i_x) to productivity and financial shocks in the lower panel, together with GMM-implied pricing errors (α^i) in percentage.

Panel A: Price of Risk				
	Data		**Model**	
	(1)	**(2)**		**(3)**
MKT	0.69	0.69	ε_a	0.75
[t]	9.33	7.43		2.01
$\varepsilon_x^{\text{Data}}$		-0.53	ε_x	-1.26
[t]		-3.16		-3.03
SSEQ (%)	5.70	5.64		0.13
MAPE (%)	5.13	5.11		0.67
J-test	9.85	9.38		5.48
p	0.83	0.86		0.38
JT-Diff		17.39		
p		0.00		

Panel B: Risk Exposure						
	L	**2**	**3**	**4**	**H**	**H-L**
Data: SDF (MKT + $\varepsilon_{\mathbf{x}}^{\mathbf{Data}}$)						
β^i_{MKT}	25.13	23.27	20.95	22.46	22.25	-2.88
[t]	14.11	10.18	13.37	7.71	11.94	-1.54
$\beta^i_{x,\text{Data}}$	3.84	0.80	-0.54	1.34	-0.99	-4.83
[t]	1.48	0.32	-0.29	0.48	-0.38	-2.62
α^i	-3.98	-0.12	-1.94	0.04	2.21	-1.42
[t]	-1.58	-0.05	-0.83	0.02	0.96	-0.60
Model: SDF ($\varepsilon_{\mathbf{a}} + \varepsilon_{\mathbf{x}}$)						
β^i_a	2.15	2.12	2.09	2.06	2.01	-0.14
[t]	9.74	8.79	7.89	6.96	5.40	-0.86
β^i_x	-5.61	-6.37	-7.14	-8.16	-9.60	-4.00
[t]	-26.12	-27.93	-28.91	-29.56	-26.93	-25.43
α^i	0.06	0.01	-0.06	-0.06	0.06	-0.02
[t]	0.36	0.02	-0.28	-0.24	0.23	-0.13