The Macro Impact of the Recovery Rate

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Abstract

This paper studies how recovery rates shape equilibrium credit allocation and aggregate outcomes in an economy with heterogeneous firms and endogenous default. Recovery rates affect lenders' expected repayment and therefore influence debt pricing, borrowing capacity, and capital accumulation. Motivated by the rise of intangible capital in the U.S. economy, we document that firms and industries with higher asset tangibility issue more debt and exhibit lower distance to default, consistent with differences in recovery values across firms. To quantify the aggregate implications, we develop a heterogeneous-firm general equilibrium model with risky debt, endogenous default, and capital investment. We structurally estimate the model using simulated method of moments (SMM), matching moments related to investment, debt issuance, credit spreads, and default rates. The baseline estimated recovery rate is 74%. Counterfactual exercises show that lower recovery rates reduce aggregate output, credit, and welfare by tightening financial constraints and limiting capital accumulation. Extending the analysis to broader measures of capital that include intangible assets yields an estimated recovery rate of 46%, implying that rising intangibility can generate economically meaningful output and welfare losses through equilibrium financial frictions and reduced borrowing capacity.

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1 Introduction

Firms rely on external financing to support capital accumulation when internal funds are insufficient to finance investment opportunities. This paper studies how recovery rates shape firms' financing decisions and the aggregate effects of financial frictions. In particular, we examine how the recovery value of capital affects equilibrium credit allocation, debt issuance, and capital accumulation in an economy with heterogeneous firms and risky debt. Motivated by the rising importance of intangible capital in the U.S. economy, we show that lower recovery rates tighten financial conditions and reduce aggregate output and welfare. To quantify these effects, we develop a quantitative heterogeneous-firm general equilibrium model with capital investment, risky debt, and endogenous default, and structurally estimate the model using firm-level financing and investment moments.

The recovery rate represents the fraction of capital value lenders can recover following firm default. This recovery value directly affects debt pricing and the equilibrium spread required by lenders, influencing firms' borrowing incentives and external financing capacity. Firms optimally choose investment and debt issuance subject to these financing conditions, implying that recovery rates jointly determine the supply of and demand for credit in equilibrium. Through this channel, variation in recovery rates shapes the magnitude of financial frictions and their aggregate consequences.

Recovery rates vary across firms and industries because the liquidation value of capital depends on both the composition and characteristics of firms' assets. One important source of variation is the rising importance of intangible capital in the U.S. economy, driven by the expansion of service and technology-oriented industries (Corrado et al. 2009; Corrado and Hulten 2010; Corrado et al. 2022). Intangible assets such as patents, software, brands, and usage rights may retain resale value and generate recovery upon default, while other forms, including organizational capital and firm-specific knowledge, are substantially less pledgeable and likely have low liquidation value. As the share of intangible capital increases, the average recovery value of firms' assets may decline, potentially affecting equilibrium credit allocation and financing conditions.

Recovery rates also depend on the physical characteristics of productive capital. Kermani and Ma (2023) show that assets that are less mobile, less durable, or more customized exhibit lower recovery values in liquidation. Their estimated industry-level recovery rates for property, plant, and equipment (PP&E) range from roughly 10% in some service industries to 70% in transportation industries, indicating substantial heterogeneity in collateral value across sectors. In addition, institutional and legal developments can alter recovery values by changing asset pledgeability. Mann (2018) finds that court decisions strengthening the collateralizability of patents relaxed financing constraints for innovative firms and expanded debt financing and investment. Together, these findings suggest that variation in recovery rates can materially affect firms' borrowing capacity and the aggregate implications of financial frictions.

At the firm level, investment decisions are shaped by financing frictions arising from costly external finance, including default risk, borrowing spreads, bankruptcy costs, and equity issuance costs. These frictions depend importantly on the recoverability of firms' assets in default. Assets with low liquidation value or limited pledgeability reduce lenders' expected recovery and increase the cost of external borrowing, thereby tightening financing conditions. To motivate the quantitative analysis, we first document empirical patterns using a CRSP-Compustat merged sample of U.S. public firms. Because firm-level recovery rates are not directly observable, we use asset tangibility as a proxy for the recoverability of capital and examine cross-sectional relationships at both the firm and industry levels. We find that firms with higher asset tangibility exhibit higher debt-to-sales ratios and lower distance to default, consistent with greater borrowing capacity and higher equilibrium credit risk when recovery values are higher. These reduced-form patterns suggest that recovery rates are closely linked to firms' financing positions, but they do not by themselves reveal the aggregate implications of changing recovery values. To quantify these effects, we develop a structural heterogeneous-firm model that allows recovery rates to shape equilibrium credit allocation and aggregate outcomes.

To quantify the aggregate implications of recovery rates and financial frictions, we develop a heterogeneous-firm general equilibrium model with capital investment, risky debt, and endogenous default. The framework builds on the dynamic corporate finance models of Strebulaev and Whited (2012) and Gilchrist et al. (2014) by embedding firms' financing and investment decisions into a general equilibrium environment. Firms differ ex post because of persistent idiosyncratic productivity shocks and optimally choose whether to default, issue debt, raise external equity, and accumulate capital. Debt prices depend on expected default losses and recovery values, implying that firms face endogenous borrowing spreads that vary with their financial positions. Investment is subject to capital adjustment costs, while external equity financing is costly. A representative household supplies labor and savings and closes the model in equilibrium.

The interaction between endogenous debt pricing, default risk, and capital accumulation makes the model analytically intractable, so we solve it numerically using the dynamic programming and discretization approach in Terry (2017). We structurally estimate the model using simulated method of moments (SMM) method, targeting moments related to profits, investment, debt issuance, credit spreads, and default rates. The identification of the recovery rate relies on equilibrium financing behavior reflected in the joint dynamics of investment and debt issuance together with observed spreads and default rates. Intuitively, recovery values influence lenders' expected repayment and therefore shape both the supply of and demand for credit in equilibrium.

We use a CRSP-Compustat merged sample covering 2001–2016 to construct the firm-level moments used in the structural estimation. The sample focuses on publicly listed U.S. firms, which are the primary participants in corporate debt and equity markets and account for a substantial share of aggregate capital investment. Using these data, we estimate the model by matching moments related to profitability, investment, debt issuance, credit spreads, and default risk. The model provides a good overall fit to the targeted financing and investment moments. In the baseline specification, the estimated recovery rate is 74%, implying substantial recoverability of productive capital in equilibrium credit markets. This estimate is higher than the average recovery values for property, plant, and equipment reported in Chapter 11 bankruptcy data suggested by Kermani and Ma (2023), consistent with the broader equilibrium interpretation of recovery embedded in the model.

Using the estimated model, we quantify how recovery rates shape aggregate outcomes through equilibrium credit allocation. We compare the baseline economy with economies characterized by lower recovery values while holding other parameters fixed. Lower recovery rates tighten financing conditions, reduce debt issuance, and constrain capital accumulation, particularly for high-productivity firms that rely more heavily on external finance. As a result, aggregate output and welfare decline, while the investment wedge increases. Quantitatively, reducing the recovery rate from 74% to 10% lowers consumption-equivalent welfare by 0.12%, reduces aggregate output by 0.6%, and increases the investment wedge by 13%. At the same time, equilibrium default rates and credit spreads decline because firms optimally reduce borrowing in response to tighter financing conditions. These results highlight that lower observed credit risk need not imply weaker financial frictions in equilibrium.

We then examine the implications of rising intangibility by broadening the definition of capital following Peters and Taylor (2017). Re-estimating the model using total capital and total investment moments yields an estimated recovery rate of 46%, substantially below the baseline estimate based primarily on physical capital. This result is consistent with the view that intangible assets are less pledgeable and generate lower recovery values in default. The estimate is also comparable to the recovery values for identifiable intangible assets documented by Kermani and Ma (2023). A counterfactual decline in the recovery rate from 74% to 46% reduces aggregate output by 0.37% and welfare by 0.11%, while simultaneously lowering equilibrium credit risk. Overall, the results suggest that rising intangible intensity can generate economically meaningful aggregate effects through its impact on recovery values and financial frictions.

This paper contributes to the macro-finance literature by quantifying the aggregate importance of recovery rates in a heterogeneous-firm economy with endogenous default. By linking recovery rates to endogenous spreads, default incentives, and capital accumulation, the model provides a quantitative framework for studying how variation in collateral recoverability affects aggregate output, welfare, and investment distortions. The paper also contributes to the growing literature on intangible capital and financing frictions. Re-estimating the model using broader measures of capital that include intangible assets yields substantially lower estimated recovery values, implying tighter equilibrium financing conditions and lower aggregate output and welfare. These results provide a quantitative macroeconomic interpretation of how rising intangible intensity can affect the economy through changes in collateral value and equilibrium credit allocation.

Related Literature. This paper relates to four strands of literature. First, the paper relates to the quantitative macroeconomic literature on financial frictions. The classic macroeconomic literature models financial frictions, often in the form of collateral constraints, as amplification mechanisms affecting firms' investment and production decisions (Gertler and Bernanke 1989; Bernanke et al. 1999; Kiyotaki and Moore 1997). More recent quantitative studies evaluate the aggregate effects of financing frictions using heterogeneous-firm models and rich micro-level data (Khan and Thomas 2013; Midrigan and Xu 2014; Jermann and Quadrini 2012). Midrigan and Xu (2014) study the role of financial frictions in misallocation and development dynamics, while Jermann and Quadrini (2012) analyze the effects of financial shocks on macroeconomic fluctuations. Gilchrist et al. (2014) quantify the interaction between uncertainty and financial frictions and estimate bankruptcy costs, and Catherine et al. (2022) use reduced-form evidence to discipline collateral constraints in a quantitative framework. Relative to this literature, the paper emphasizes recovery rates as an equilibrium determinant of credit allocation and identifies recovery values using moments jointly related to investment, debt issuance, spreads, and default risk.

Second, the paper relates to the literature on intangible capital and corporate finance. Eisfeldt and Papanikolaou (2013) study the relationship between organizational capital and expected stock returns. Peters and Taylor (2017) show that incorporating intangible capital improves the empirical performance of investment models, while Falato et al. (2022) document important connections between intangible capital, debt capacity, and corporate liquidity management. Relative to this literature, the paper provides a quantitative macroeconomic framework linking intangible intensity to financing conditions through the recovery-rate channel. In particular, the paper structurally estimates the recovery value of broader measures of capital that include intangible assets and evaluates the aggregate implications of lower collateral recoverability.

Third, the paper relates to the structural corporate finance literature studying firms' financing, investment, and default decisions. Hennessy and Whited (2005) develop a dynamic trade-off model to explain firms' financing behavior and estimate the pledgeability of physical assets, while Hennessy and Whited (2007) incorporate endogenous default and bankruptcy costs into a structural framework. Strebulaev and Whited (2012) provide a comprehensive overview of dynamic structural corporate finance models and estimation methods. Relative to this literature, the paper embeds firms' financing and default decisions into a general equilibrium environment and studies how recovery values shape equilibrium credit conditions and aggregate outcomes.

Finally, the paper relates to finance studies examining asset pledgeability and debt capacity. Mann (2018) show that increases in patent collateral value relax financing constraints and support debt financing for innovative firms, while Chava et al. (2017) find that improvements in patent collateral value reduce borrowing costs. Kermani and Ma (2020) study firms' liquidation values and show that both asset pledgeability and cash-flow-based borrowing capacity affect debt capacity. Relative to these studies, the paper provides a model-based estimate of recovery values within a quantitative equilibrium framework featuring endogenous default and risky debt pricing, allowing the analysis of aggregate implications of changing collateral recoverability and financing conditions.

The remainder of the paper proceeds as follows. Section 2 describes the data and presents motivating empirical evidence on the relationship between recovery values and firms' financial positions. Section 3 develops the heterogeneous-firm general equilibrium model with capital investment, risky debt, and endogenous default. Section 4 outlines the structural estimation procedure and presents the baseline estimation results. Section 5 uses the estimated model to quantify the aggregate implications of varying recovery rates for credit allocation, output, welfare, and investment distortions. Section 6 extends the analysis to broader measures of capital that include intangible assets and examines the implications of lower recovery values associated with rising intangible intensity. Section 7 concludes. Additional details regarding the data, model solution, and estimation procedure are provided in the Appendix.

2 Data and Stylized Facts

This section presents motivating empirical evidence on the relationship between recovery values and firms' financing positions. In the framework developed later in the paper, recovery rates affect lenders' expected repayment and therefore influence debt pricing, borrowing capacity, and firms' investment decisions. Holding borrowing fixed, lower recovery values increase financing frictions by raising equilibrium borrowing spreads and default losses. At the same time, equilibrium credit risk need not decline when recovery values are high, since improved borrowing conditions can stimulate credit demand and increase leverage. To study these mechanisms empirically, I examine the relationship between asset tangibility, which proxies for the recoverability of capital, and firms' financing outcomes using U.S. public firm data. The evidence is intended to provide suggestive support for the model mechanism rather than causal identification. We document that firms with higher asset tangibility exhibit higher debt-to-sales ratios and lower distance to default, consistent with greater borrowing capacity and higher equilibrium credit risk when recovery values are higher.

2.1 Data Description

We construct an annual panel of publicly listed U.S. firms from the CRSP-Compustat merged database over the period 1987–2016 following standard sample-selection procedures in the corporate finance literature.[2] The dataset is well suited for the analysis for two reasons. First, the long panel dimension allows the construction of firm-level moments capturing variation in investment, financing, and profitability for structural estimation. Second, the balance-sheet information permits the measurement of firms' capital composition, financing positions, and external borrowing activity.

We begin by constructing measures of firms' physical and intangible capital stocks. Physical capital is measured using the net book value of property, plant, and equipment (CRSP-Compustat variable *ppent*). In addition to physical assets, firms accumulate intangible capital through investments in knowledge, organizational structure, software, brands, and other nonphysical assets. Following Peters and Taylor (2017) and Falato et al. (2022), we treat intangible investment as contributing to the accumulation of productive capital rather than directly augmenting productivity. This approach is appropriate for the present analysis because the paper focuses on how differences in recoverability across asset types affect financing conditions and equilibrium credit allocation.

Measuring intangible capital is challenging because internally generated intangible assets are generally not recorded on firms' balance sheets. To address this issue, we incorporate the intangible capital measures constructed by Peters and Taylor (2017), who estimate firms' internally generated intangible capital using a perpetual inventory approach based on the accumulation of past intangible investments. Their methodology distinguishes between knowledge capital and organizational capital. We define total intangible capital as the sum of these two components and merge the resulting estimates into the CRSP-Compustat sample. Firm-level asset tangibility is then defined as the ratio of physical capital to total capital, where total capital is the sum of physical and intangible capital. Figure 1 shows that average asset tangibility in the sample declines by roughly 10% between 1987 and 2016, consistent with the rise of intangible capital documented in the studies using aggregate data (Corrado and Hulten 2010, 2014).

[2] Appendix B provides details of the data construction procedure.

[Insert Figure 1 Here]

Firms accumulate capital through both physical and intangible investment. Physical investment is measured using capital expenditures (CRSP-Compustat variable *capx*). To construct measures of intangible investment, we follow the methodology in Peters and Taylor (2017). Firms accumulate knowledge capital through research and development expenditures (CRSP-Compustat variable *xrd*) and organizational capital through expenditures related to selling, general, and administrative activities (CRSP-Compustat variable *xsga*). Following the convention in the recent literature (Hulten and Hao 2008; Eisfeldt and Papanikolaou 2014; Peters and Taylor 2017), we classify 30% of SG&A expenditures as investment in organizational capital and treat the remaining component as operating expenses. Total intangible investment is then defined as the sum of investment in knowledge capital and organizational capital.

To characterize firms' financing positions, we construct two measures related to external borrowing and credit risk: the debt-to-sales ratio and distance to default. The debt-to-sales ratio measures firms' reliance on external debt financing and is defined using total debt outstanding, calculated as the sum of long-term debt (CRSP-Compustat variable *dltt*) and short-term debt (CRSP-Compustat variable *dlc*), scaled by firm sales. This unit-free measure facilitates comparisons across firms with different sizes and industry characteristics.

To measure firms' credit risk, we construct a distance-to-default measure based on the Merton framework. Distance to default measures how many standard deviations a firm's asset value must decline relative to its debt obligations before default occurs. The measure provides a forward-looking proxy for default risk and has been shown to explain variation in corporate bond spreads and credit market conditions (Gilchrist and Zakrajšek 2012; Atkeson et al. 2017). The construction of the measure requires information on firms' debt levels, equity values, stock prices, and equity volatility, which we obtain by merging CRSP daily securities data with Compustat quarterly fundamentals data. We follow the iterative procedure in Gilchrist and Zakrajšek (2012) and Ottonello and Winberry (2020) to compute firms' one-year-ahead distance to default. This measure is also widely used in practice, including in Moody's KMV framework for estimating expected default frequencies. In the absence of comprehensive bond-level information for all firms in the sample, distance to default provides a useful firm-level proxy for default risk and equilibrium credit conditions.

Table 1 reports summary statistics for the sample used in the reduced-form analysis. Firms in the sample are large, with average annual sales of $7,282 million and average physical capital stock of $2,679 million. Average debt outstanding is $1,926 million, indicating that external debt financing represents a quantitatively important component of firms' balance sheets. Physical and intangible investment rates are similar on average and display comparable volatility. The mean asset tangibility ratio is 0.55, implying that approximately 45% of firms' total capital consists of intangible assets on average.

The summary statistics also indicate substantial heterogeneity in firms' financing positions and credit risk. The average debt-to-sales ratio is 1.77, while the average distance to default is 6.47. This level of distance to default is comparable to estimates reported in Gilchrist and Zakrajšek (2012) and Ottonello and Winberry (2020), suggesting that the average firm would require a sufficiently large adverse shock to experience default within a one-year horizon. The debt measures additionally exhibit substantial dispersion across firms, highlighting meaningful variation in leverage and financing conditions within the sample. In the structural estimation exercises in Section 4, we focus on the post-2001 subsample to construct the moments targeted in the estimation procedure.

[**Insert Table 1 Here**]

2.2 Asset Tangibility

This subsection examines the cross-sectional relationship between firms' asset tangibility and their financing positions in both the short run and the long run. Asset tangibility measures the share of firms' capital stock accounted for by physical assets, while the debt-to-sales ratio captures firms' reliance on external debt financing. Distance to default provides a forward-looking measure of credit risk, with higher values indicating that larger adverse shocks are required for default to occur. We document two central empirical patterns: firms with higher asset tangibility exhibit higher debt-to-sales ratios and lower distance to default. These patterns are consistent with the view that differences in collateral recoverability shape firms' borrowing capacity and equilibrium financing conditions.

Firm-level asset tangibility is defined as the ratio of physical capital to total capital, where total capital includes both physical and intangible assets. Intangible assets differ substantially in their recoverability and pledgeability. Certain forms of intangible capital, such as patents, technologies, brands, and usage rights, are identifiable and may retain liquidation value in secondary markets. Kermani and Ma (2023) show that the recovery values of identifiable intangible assets are quantitatively comparable to those of physical capital, with average recovery rates around 35%. In contrast, organizational capital and firm-specific human capital are considerably less transferable and are generally believed to have low liquidation value in default. Using the estimates in Peters and Taylor (2017), organizational capital accounts for the majority of firms' intangible capital on average. As a result, firms with lower asset tangibility are likely to have lower effective recovery values and face tighter financing conditions in equilibrium.

We first examine the relationship between asset tangibility and firms' reliance on external debt financing. Figure 2 presents cross-sectional evidence at both the industry and firm levels using averages over the full sample period. Panel A reports a binned scatterplot of industry-level averages constructed using three-digit SIC industries, together with the corresponding fitted regression line. The sample contains 209 industries. Panel B presents the analogous relationship at the firm level using 1,142 firms. In both cases, firms and industries with higher asset tangibility exhibit higher debt-to-sales ratios, indicating greater use of external debt financing. Quantitatively, the estimated relationship implies that a one-standard-deviation increase in asset tangibility is associated with approximately 12.5% higher debt-to-sales ratios relative to the sample mean.

To examine whether the relationship also holds within firms over time, we estimate panel regressions of the debt-to-sales ratio on asset tangibility with firm and year fixed effects. Columns (3) and (6) of Table 2 show that the positive relationship remains statistically significant in the short run after controlling for time-invariant firm characteristics and aggregate shocks. Taken together, the long-run and short-run evidence suggests that firms with lower collateral recoverability tend to rely less on external debt financing and face tighter equilibrium borrowing conditions.

We next examine the relationship between asset tangibility and firms' credit risk using distance to default. Figure 3 presents binned scatterplots relating asset tangibility to distance to default at both the industry and firm levels. In both cases, the relationship is negative: firms and industries with higher asset tangibility tend to exhibit lower distance to default and therefore higher equilibrium credit risk. Quantitatively, the estimated relationship implies that a one-standard-deviation increase in asset tangibility is associated with approximately 11.03% lower distance to default relative to the sample mean.

Table 3 reports the corresponding panel regression results examining within-firm variation over time. After controlling for firm and year fixed effects, the estimated coefficients on asset tangibility remain negative but are imprecisely estimated. One interpretation is that firms with relatively low asset tangibility tend to borrow less and therefore maintain persistently low default risk, limiting within-firm variation in distance to default over time. Overall, the evidence suggests that firms with higher recovery values may simultaneously sustain higher leverage and higher equilibrium credit risk because improved borrowing conditions increase credit demand.

Third, we complement the baseline analysis by incorporating information on bond market pricing and forward-looking default risk. To do so, we merge the CRSP-Compustat sample with data from FISD-TRACE and NUS-CRI. FISD-TRACE provides information on corporate bond issuance and transactions, allowing the construction of bond credit spreads measured as the difference between corporate bond yields to maturity and comparable Treasury yields. NUS-CRI provides forward-looking estimates of firms' probabilities of default based on macro-financial conditions and firm-specific characteristics. Due to data availability, the merged sample covers the period from 2002 to 2016.

Using firm-level averages from the merged sample, we construct binned scatterplots relating asset tangibility to these alternative measures of credit risk. Figure 4 shows that firms with higher asset tangibility exhibit both higher credit spreads and higher probabilities of default. These findings are consistent with the equilibrium mechanism emphasized in the paper: higher recovery values relax financing constraints and increase firms' borrowing capacity, which can lead to greater leverage and higher equilibrium credit risk despite lower expected losses conditional on default.

The empirical patterns documented in this section reveal a robust positive relationship between asset tangibility and firms' debt usage, together with a negative relationship between asset tangibility and distance to default. These relationships hold both across firms in the long run and within firms over time. The evidence is consistent with the view that firms with lower recovery values face tighter financing conditions and therefore rely less on external borrowing in equilibrium. At the same time, firms with higher recovery values can sustain both higher leverage and higher equilibrium credit risk because improved borrowing conditions stimulate credit demand and increase debt issuance. While these reduced-form relationships are not intended to establish causal effects, they motivate the central mechanism of the paper and provide empirical discipline for the quantitative framework developed in the following sections. The model uses these financing and credit-risk moments to identify recovery values and quantify their aggregate implications for credit allocation, output, and welfare.

[**Insert Figure 2 Here**]

[**Insert Table 2 Here**]

[**Insert Figure 3 Here**]

[**Insert Table 3 Here**]

[**Insert Figure 4 Here**]

3 Model

We develop a heterogeneous-firm general equilibrium model with risky debt and endogenous default to study how recovery values shape equilibrium credit allocation and aggregate outcomes. The framework is a quantitative neoclassical model featuring firm heterogeneity, capital adjustment costs, and financing frictions. Firms use capital and labor to produce output, accumulate capital subject to adjustment costs, and finance investment through a combination of internal funds, risky debt, and costly external equity issuance. Firms may optimally default on outstanding debt, in which case lenders recover only a fraction of firm capital. The recovery value of capital therefore directly affects debt pricing, borrowing conditions, and firms' financing decisions in equilibrium.

The economy consists of three types of agents: firms, competitive lenders, and a representative household. Firms differ because of persistent idiosyncratic productivity shocks and optimally choose labor demand, investment, debt issuance, equity issuance, and default decisions. Competitive risk-neutral lenders price risky debt based on expected repayment and recovery values. A representative household supplies labor, owns firms, and provides savings to the credit market. Time is discrete. Prime notation ($'$) denotes future-period variables. Uppercase variables refer to aggregate quantities, while lowercase variables denote firm-level objects unless state variables are explicitly shown in parentheses.

3.1 Firms

Each firm is characterized by an idiosyncratic productivity level z and produces output using capital and labor under decreasing returns to scale. Production is given by the Cobb-Douglas technology

$$y = zk^{\alpha}n^{\nu}, \quad \alpha + \nu < 1. \tag{1}$$

where k denotes capital and n denotes labor input. Firm-level productivity evolves according to a persistent AR(1) process,

$$\log z' = \rho_z \log z + \varepsilon_z^{'} \,, \quad \varepsilon_z^{'} \sim N(0, \sigma_z^2) \,, \quad 0 < \rho_z < 1. \tag{2}$$

Persistent productivity heterogeneity generates variation in firms' investment opportunities, financing demand, and default incentives.

Firms accumulate capital through investment subject to one-period time-to-build and depreciation,

$$k' = (1 - \delta)k + i, \quad 0 < \delta < 1.$$

where i denotes current investment expenditure. Investment is costly to adjust and entails quadratic adjustment costs of the form $AC(k, i) = \frac{\phi}{2}(\frac{i}{k})^2 k$. These adjustment costs generate gradual capital accumulation dynamics and create incentives for firms to smooth investment and financing decisions over time.

Firms operate in competitive factor and goods markets and become heterogeneous over time because of persistent idiosyncratic productivity shocks. A firm's state is characterized by its productivity z, capital stock k, and outstanding debt obligations b. At the beginning of each period, firms decide whether to repay or default on previously issued debt. In the event of default, lenders recover a fraction of the firm's depreciated capital net of deadweight default costs. The firm subsequently re-enters production in the following period with zero capital and debt while retaining its productivity state. The quantitative results are robust to alternative specifications in which defaulting firms draw new productivity levels upon re-entry.

Firms that repay outstanding debt continue operating and choose investment, labor demand, debt issuance, and external equity financing. Labor is hired competitively at wage rate W, while new one-period debt is priced by lenders according to expected repayment and recovery values. Firms maximize the expected discounted value of current and future payouts to shareholders, where the stochastic discount factor is determined by the equilibrium real interest rate r satisfying $(1+r)^{-1} < 1$. Through firms' optimal financing and default decisions, recovery values directly affect equilibrium borrowing conditions, leverage, and capital accumulation.

The firm distributes dividends to shareholders according to

$$d = e(z, k, k', b, b') - \eta(e(z, k, k', b, b')), \tag{3}$$

where $e(\cdot)$ denotes internal cash flow before equity issuance costs and $\eta(\cdot)$ captures the costs associated with external equity financing. Firm cash flow is given by

$$\begin{aligned} e =& (1-\tau)[y - AC(k, i) - Wn] \\ &+ q(z, k', b')b' - b - i + \tau(rb + \delta k). \end{aligned}$$

Current cash flow consists of after-tax operating profits net of investment adjustment costs and labor payments, together with net resources raised through debt issuance. Firms repay existing debt obligations b, finance new investment i, and receive tax shields associated with interest payments and capital depreciation. The price of newly issued debt, $q(z, k', b')$, depends on firms' future repayment probabilities and recovery values, implying that financing conditions are endogenously linked to firms' balance-sheet positions and default incentives.

When internal cash flow is insufficient to finance investment and debt repayment, firms issue external equity. Equity issuance is costly and follows the specification $\eta(e) = \eta_1 |e| \mathbb{1}_{e<0}$, where η_1 denotes the proportional cost of external equity finance. This reduced-form specification captures issuance costs arising from underwriting expenses and adverse selection frictions, following Gomes and Schmid (2010).

Operating profits consist of output net of labor costs and capital adjustment costs, after corporate income taxation at rate $\tau \in (0, 1)$. Firms finance investment by combining internal funds with external debt issuance. New debt issuance of face value b' is sold at price $q(z, k', b')$, generating proceeds equal to $q(z, k', b')b'$, while previously issued debt b must be repaid in full absent default. Firms additionally benefit from tax shields associated with depreciation allowances and interest deductibility. Because debt prices depend on expected repayment and recovery values, firms' financing choices are jointly determined with equilibrium borrowing conditions.

Given the firm's state (z, k, b), default occurs when realized net worth falls below zero and the firm is unable to repay its outstanding debt obligations.[3] Realized net worth is defined as the value of current operating resources and undepreciated capital net of outstanding debt obligations:

$$x = zk^{\alpha}n^{\nu} - Wn + (1-\delta)k - b. \tag{4}$$

Combining the expression for realized net worth with the default condition $x \leq \bar{x} = 0$ yields a productivity threshold $z^D(k, b)$ below which the firm defaults, conditional on its capital stock and outstanding debt obligations:

$$z^D(k, b) \equiv \left[\frac{\bar{x} + b - (1-\delta)k}{(1-\nu)(\frac{\nu}{W})^{\frac{\nu}{1-\nu}} k^{\frac{\alpha}{1-\nu}}} \right]^{1-\nu}. \tag{5}$$

The default threshold is increasing in leverage and decreasing in the productive capacity of the firm. Firms with larger debt burdens require higher productivity realizations to remain solvent, while firms with larger capital stocks are better able to generate operating profits sufficient to service debt obligations. Because lenders price debt according to expected default probabilities and recovery values, this endogenous default cutoff directly affects equilibrium borrowing conditions and firms' financing choices.

The firm's optimization problem can be written recursively. Upon entering the current period, the firm chooses whether to continue operating or default on its outstanding debt

[3] The default threshold is defined in terms of realized net worth rather than limited liability as in Gilchrist et al. (2014). This specification can be interpreted as a reduced-form representation of financial covenant violations triggering default. It is also closely related to settings in which default occurs when the value of equity reaches a lower bound in partial equilibrium models with i.i.d. productivity shocks. Empirically, it is not clear whether firms declare bankruptcy based on negative market equity values or negative net asset values. Computationally, this assumption substantially simplifies the solution of the model by avoiding the need to solve for endogenous default thresholds and debt pricing functions within each iteration of the dynamic programming routine, which is particularly costly in the general equilibrium SMM estimation framework considered here.

obligations. The value function is given by

$$V(z,k,b) = \begin{cases} V_{ND}(z,k,b), & z \geq z^D(k,b), \\ V_D(z), & z < z^D(k,b), \end{cases} \tag{6}$$

where $V_{ND}(z,k,b)$ denotes the continuation value associated with repayment and continued operation, while $V_D(z)$ denotes the value of default. Conditional on repayment, the firm chooses future capital and debt issuance to maximize the expected discounted value of shareholder payouts:

$$V_{ND}(z,k,b) = \max_{\{k',b'\}} d + \frac{1}{1+r} E[V(z',k',b')|z]. \tag{7}$$

The continuation value reflects the joint determination of investment, financing, and default decisions in the presence of risky debt and endogenous borrowing spreads. Since labor adjustment is frictionless, labor demand is chosen intratemporally as a static function of the current state (z,k,b).

If the firm defaults, lenders seize the firm's undepreciated capital net of deadweight default costs, and the firm exits the current financial position. In the following period, the firm re-enters production with zero capital and zero debt:

$$V_D(z) = \left\{ 0 + \frac{1}{1+r} E[V(z',0,0)|z] \right\} \tag{8}$$

The value of default therefore reflects the continuation value associated with restarting operations after balance-sheet restructuring. Equations (5)–(8) jointly determine the firm's endogenous default policy $df(z,k,b)$ together with the optimal investment and debt issuance policies, $k'(z,k,b)$ and $b'(z,k,b)$, conditional on repayment. Through these policy functions, firms' financing and default decisions interact with equilibrium debt pricing and recovery values.

3.2 Lenders

Firms obtain external debt financing from competitive risk-neutral lenders who require an expected return equal to the risk-free interest rate r. Lenders fully internalize firms' endogenous default decisions when pricing debt contracts and therefore condition debt prices on the firm's state (z,k,b) and future repayment probabilities. In the event of default, lenders recover a fraction of the firm's undepreciated capital stock net of deadweight default costs. The recovery ratio on debt is given by

$$R(k', b') = \left[\frac{(1-\tau)\gamma(1-\delta)k'}{b'}\right],$$

where $\gamma \in (0, 1)$ denotes the fraction of capital recoverable upon default. Lower recovery values therefore reduce lenders' expected repayment and tighten equilibrium borrowing conditions. We assume that recovered assets are liquidated and transferred to lenders at the end of the period following default.

The price of risky debt, $q(z, k', b')$, is determined endogenously such that competitive lenders earn the risk-free rate in expectation. The zero-profit condition for lenders is given by

$$q(z, k', b') = \frac{1}{1+r} E[1 + df(z', k', b')(R(k', b') - 1)|z]. \tag{9}$$

Debt prices therefore depend on firms' expected default probabilities and recovery values. A lower recovery rate reduces lenders' expected repayment conditional on default and leads to lower debt prices and tighter borrowing conditions in equilibrium.

The corresponding credit spread, defined as the difference between the firm's borrowing rate and the risk-free rate, is

$$S(z, k', b') = \frac{1}{q(z, k', b')} - (1 + r).$$

Because debt pricing is state dependent, firms with higher leverage, lower productivity, or lower recovery values face higher equilibrium borrowing spreads. Through this channel, recovery values directly affect firms' financing costs, debt issuance decisions, and capital accumulation.

3.3 Households

To close the model, the economy is populated by a continuum of identical households with unit measure. Because households are ex ante identical and face the same optimization problem, aggregate household behavior can be represented by a single representative household. Given the equilibrium wage rate W and real interest rate r, the representative household solves a standard infinite-horizon consumption-savings problem:

$$\begin{aligned} &\max_{\{N_{t+s}, B_{t+s+1}\}_{s=0}^{\infty}} \beta^s (\log C_{t+s} - \psi N_{t+s}) \quad s.t. \\ &C_{t+s} + \frac{B_{t+s+1}}{1+r} = W N_{t+s} + B_{t+s} + \int d_{t+s}(z, k, b) dF_{t+s}(z, k, b) + T_{t+s}\ , \end{aligned} \tag{10}$$

where $d(z,k,b)$ denotes firm dividends and T denotes lump-sum transfers financed through tax revenues. Household income consists of labor earnings WN, returns from savings B, aggregate firm dividends $D = \int d(z,k,b)dF$ and government transfers T. The household allocates these resources between current consumption C and risk-free savings B'. Through its savings decisions, the representative household supplies funds to the credit market and determines the equilibrium risk-free interest rate.

The representative household's optimization problem yields standard Euler and labor supply conditions:

$$\frac{1}{C_{t+s}} = \beta(1+r)\frac{1}{C_{t+s+1}}, \quad \frac{1}{C_{t+s}}W = \psi.$$

The first condition determines the intertemporal trade-off between current and future consumption, while the second pins down labor supply through the marginal rate of substitution between consumption and leisure.

Because the model contains no aggregate uncertainty, the equilibrium is stationary and aggregate quantities remain constant over time. Imposing stationarity simplifies the household optimality conditions to

$$C_{t+s} = C, \quad r = \frac{1}{\beta} - 1, \quad W = \psi C.$$

The equilibrium real interest rate is therefore determined by the household discount factor, while the equilibrium wage is proportional to aggregate consumption.

3.4 Stationary Competitive Equilibrium

A stationary competitive equilibrium consists of equilibrium prices W, r, a debt pricing schedule q, aggregate quantities C, Y, I, ACK, ACE, firm value functions V, V_{ND}, V_D, policy functions k', b', df, and a stationary distribution of firms $F(z,k,b)$ such that: (1) the representative household optimizes consumption, labor supply, and savings decisions given equilibrium prices W and r; (2) taking W, r, q as given, firms optimally choose investment, debt issuance, equity issuance, labor demand, and default decisions, and the associated value and policy functions solve the firms' dynamic optimization problem; (3) the labor market clears: $N = \int n(z,k,b)dF(z,k,b)$; (4) the bond market clears: $B = 0$; (5) the goods market clears:

$$\begin{aligned} C &= Y - I - ACK - ACE \\ &= \int \Big\{ y(z,k,b) - i(z,k,b) - AC(k,i) - \eta(z,k,b) \Big\} dF; \end{aligned}$$

(6) the stationary distribution of firms $F(z, k, b)$ is invariant over time under the equilibrium policy rules and the stochastic process governing firm-level productivity. In equilibrium, recovery values influence debt pricing and firms' financing decisions, which in turn shape the stationary distribution of leverage, default risk, and capital allocation across firms.

3.5 Solving the Model

A solution to the model consists of equilibrium firm policy functions k', b', df, value functions V, V_{ND}, V_D, a state-dependent debt pricing schedule q, and equilibrium prices W, r. Because the model features heterogeneous firms, endogenous default, and equilibrium debt pricing, it does not admit a closed-form solution. We therefore solve the model numerically using standard dynamic programming techniques, with additional implementation details provided in Appendix A.1.

The state space for firm productivity, capital, and debt (z, k, b) is discretized. The continuous AR(1) productivity process is approximated by a discrete-state Markov chain using the method of Tauchen (1986). The numerical procedure proceeds iteratively. We begin with an initial guess for the equilibrium wage rate W, which implies an aggregate consumption level consistent with the representative household's optimality conditions. Taking equilibrium prices as given, firms solve their dynamic optimization problem using policy function iteration, generating optimal investment, borrowing, and default decisions together with the associated debt pricing schedule. Given the resulting policy rules, We compute the stationary distribution of firms and aggregate quantities implied by the model. The wage rate is then updated until the implied aggregate consumption satisfies goods market clearing within a prespecified tolerance level. The fixed point of this procedure determines the stationary competitive equilibrium.

4 Structural Estimation

4.1 Estimation Procedure

We estimate the model using the Simulated Method of Moments (SMM) because the heterogeneous-firm equilibrium framework does not admit a closed-form solution. The estimation procedure chooses the parameter vector $\hat{\theta}$ to minimize the weighted distance between empirical moments $m(X)$ computed from the data and model-generated moments $m_S(\theta)$ obtained from simulated data:

$$\hat{\theta} = argmin_{\theta}(m(X) - m_S(\theta))'W(m(X) - m_S(\theta)) \tag{11}$$

The weighting matrix W is given by the inverse of the variance-covariance matrix of the empirical moments, yielding an asymptotically efficient SMM estimator. The estimation strategy disciplines the model using moments jointly related to firms' investment, financing, and default behavior, allowing the recovery rate parameter to be identified through its effects on equilibrium credit allocation and debt pricing. Additional details regarding the estimation procedure are provided in Appendix C.

4.2 Externally Fixed and Estimated Parameters

The model contains 11 parameters summarized in Tables 4 and 6. Following the standard approach in the quantitative macro-finance literature, we calibrate six parameters externally using values from the literature or direct empirical counterparts and estimate the remaining five parameters structurally using simulated method of moments.

The externally calibrated parameters are set as follows. The risk-free interest rate r is fixed at 4%, while the corporate income tax rate τ is set to 20%. The household labor disutility parameter ψ is calibrated to 2.0 to match the target that households spend approximately one-third of available time working. The depreciation rate of physical capital is set to 0.12 following Falato et al. (2022). On the production side, the labor revenue elasticity ν is fixed at 0.50 and the capital revenue elasticity α at 0.25, consistent with the estimates in Bloom et al. (2018).

The remaining five parameters are estimated by matching moments related to firms' profitability, investment, financing, and default behavior. These parameters include the persistence and volatility of idiosyncratic productivity shocks, (ρ_z, σ_z), the capital adjustment cost parameter ϕ, the external equity issuance cost parameter η_1, and the recovery rate parameter γ. The recovery rate is the key parameter of interest because it governs lenders' expected repayment, equilibrium debt pricing, and firms' borrowing capacity within the model.

[**Insert Table 4 Here**]

4.3 Data Moments

A central step in the SMM procedure is the selection of moments used to discipline the model. Hennessy and Whited (2007) emphasize that informative moments should be sensitive to the parameters being estimated, economically meaningful, and closely connected to firms' technological and financing decisions. Poorly chosen moments can weaken identification and lead to imprecise parameter estimates. In the present framework, the targeted moments are selected to jointly capture firms' profitability, investment behavior, financing choices, and default risk, all of which are directly influenced by equilibrium debt pricing and recovery values.

We estimate the model parameters by targeting the moments reported in Table 5, initially focusing on specifications using physical capital only. The empirical moments are constructed from the CRSP-Compustat merged sample described in Section 2. The targeted micro moments consist of the variance-covariance structure of profits, investment rates, and debt issuance, while the targeted macro moments include the average credit spread and average default rate. These moments are informative about both the technological parameters governing firm dynamics and the financial parameters shaping borrowing conditions. In particular, the joint behavior of investment, debt issuance, spreads, and default frequencies helps identify the recovery rate parameter through its effects on equilibrium credit allocation and firms' financing decisions.

[**Insert Table 5 Here**]

Although the targeted moments jointly contain information about all estimated parameters, certain moments are particularly informative for specific dimensions of the model. Moments related to firm profitability help identify the persistence and volatility of idiosyncratic productivity shocks, (ρ_z, σ_z). In particular, higher productivity volatility directly increases the dispersion of firm profits, while greater persistence affects the dynamics of investment and financing decisions over time. Moments involving investment volatility and the covariance between investment and profitability are informative about the capital adjustment cost parameter ϕ. Higher adjustment costs smooth firms' investment responses to productivity shocks, reducing the responsiveness of capital accumulation and altering the joint dynamics of profits and investment.

Moments related to debt issuance and borrowing spreads are informative about the cost of external equity finance, η_1. The equity issuance cost parameter influences firms' reliance on debt relative to equity financing and therefore affects both leverage dynamics and equilibrium borrowing behavior. More broadly, the interaction between firms' financing choices and debt pricing helps discipline the financial side of the model.

The recovery rate parameter γ is primarily identified through moments related to equilibrium credit allocation and default risk. In particular, the average credit spread, the average default rate, and the correlation between investment and debt issuance are highly sensitive to changes in recovery values. Figure 5 illustrates the local identification of γ around the baseline SMM estimates. Higher recovery values increase lenders' expected repayment conditional on default, relaxing borrowing conditions and allowing firms to sustain greater leverage. As a result, both equilibrium credit spreads and default frequencies increase with γ because firms optimally expand borrowing when financing conditions improve. At the same time, the correlation between investment and debt issuance declines as recovery values rise, reflecting weaker financing constraints and greater flexibility in firms' borrowing decisions. When recovery values are low, firms issue debt primarily when investment needs are sufficiently strong to justify the higher marginal financing costs. These moments therefore jointly identify the recovery rate through its effects on equilibrium debt pricing, borrowing capacity, and firms' financing behavior.

[**Insert Figure 5 Here**]

4.4 Estimation Results

Table 6 reports the baseline SMM parameter estimates and associated standard errors. The estimated persistence and volatility of firm-level productivity are 0.7560 and 0.1606, respectively, broadly consistent with estimates of AR(1) productivity processes in the macroeconomics and corporate finance literature (Hennessy and Whited 2007; Khan and Thomas 2013). The estimated capital adjustment cost parameter is $\phi = 4.0596$, implying meaningful smoothing in firms' investment dynamics. The estimated external equity issuance cost is 0.0674, close to the estimate for large firms reported in Hennessy and Whited (2007). Relative to some alternative estimates in the literature, the value obtained here is somewhat larger, reflecting differences in specification. In particular, the present framework includes only proportional equity issuance costs and does not separately model fixed issuance costs, which are difficult to identify jointly with proportional costs using the targeted moments.

The estimated recovery rate of capital is 0.7404, implying that lenders recover approximately 74% of the after-tax undepreciated value of capital in the event of default. This estimate lies near the upper range of the recovery values reported in Kermani and Ma (2023), while remaining below the externally calibrated value used in Hennessy and Whited (2007). Within the model, the recovery rate is a key determinant of equilibrium debt pricing and borrowing capacity, affecting both firms' financing choices and aggregate credit allocation.

Table 7 evaluates the overall fit of the model by comparing model-implied moments with their empirical counterparts. Despite the nonlinear and overidentified structure of the estimation problem, the model matches the targeted financing and investment moments reasonably well, including average credit spreads and default frequencies. The model therefore captures key dimensions of firms' financing behavior and equilibrium credit conditions in the data. Some discrepancies remain. In particular, the model understates the volatility of firm profits and overstates the correlation between profitability and debt issuance. One interpretation is that observed profits contain additional transitory variation or accounting-related noise not captured by the model. More generally, because the framework relies on a single productivity shock to generate firm-level dynamics, profitability, investment, and financing decisions are tightly linked in equilibrium. Introducing additional shocks or richer financing frictions could improve the fit along these dimensions. Finally, the optimal weighting matrix assigns relatively small weight to moments with large sampling uncertainty, such as the covariance between profits and debt issuance, contributing to larger discrepancies for those moments in the estimated model. Section 6 shows that the model fit improves further when estimation targets are constructed using broader measures of total capital that include intangible assets.

[**Insert Table 6 Here**]

[**Insert Table 7 Here**]

4.5 Firm Value and Optimal Firm Decisions

Figure 6 plots cross-sections of the firm value function from the baseline estimation as a function of capital stock for different levels of idiosyncratic productivity, holding the debt-to-capital ratio fixed at its median value in the stationary distribution. Firm value increases with both productivity and capital accumulation, reflecting higher expected future profits and improved financing capacity for more productive firms with larger capital stocks.

[**Insert Figure 6 Here**]

To illustrate the model's optimal financing and investment decisions, Figure 7 reports the policy functions for capital accumulation and debt issuance as functions of firm-level productivity. The policy functions are evaluated at the average values of capital and debt in the stationary distribution, with variables expressed as log deviations from their corresponding ergodic means. Parameters are fixed at the calibrated and estimated values reported in Section 4. The figure shows that both optimal capital accumulation and debt issuance increase with firm productivity. More productive firms face stronger investment incentives, borrow more in equilibrium, and accumulate larger capital positions because higher expected future profitability improves repayment capacity and relaxes effective financing constraints.

[**Insert Figure 7 Here**]

[**Insert Figure 8 Here**]

Figure 8 illustrates how equilibrium debt prices and borrowing spreads vary with firms' leverage positions. Panel A shows that the price of debt declines as the debt-to-capital ratio increases. Higher leverage raises firms' default probabilities and lowers lenders' expected repayment, reducing the equilibrium price at which debt can be issued. Panel B reports the corresponding credit spread as a function of the debt-to-capital ratio. Holding productivity and capital fixed, firms with higher leverage face higher borrowing spreads because lenders require additional compensation for increased default risk. The figure therefore illustrates how financing costs rise endogenously with leverage through the equilibrium pricing of risky debt.

5 Recovery Rates, Credit Allocation, and Aggregate Outcomes

5.1 Aggregate Implications of Recovery Rates

This subsection quantifies the aggregate implications of changes in recovery values using a series of counterfactual exercises. We evaluate how variation in the recovery rate of capital affects equilibrium credit allocation, aggregate output, welfare, aggregate debt issuance, and the investment wedge. We additionally examine the behavior of average credit spreads and default rates to characterize equilibrium credit risk. In these exercises, all parameters other than the recovery rate are fixed at their baseline SMM estimates, allowing the analysis to isolate the quantitative role of collateral recoverability in shaping financing conditions and aggregate outcomes.

Figure 9 plots the equilibrium average spread and default rate for economies with different recovery rates. When the recovery rate is low, lenders recover only a small fraction of firm capital in default states, reducing expected repayment and generating high borrowing spreads. However, both the average spread and the default rate increase as the recovery rate rises around the baseline estimated value of γ. This pattern reflects the endogenous response of firms' borrowing behavior. Higher recovery values relax financing constraints and increase firms' borrowing capacity, leading firms to issue more debt in equilibrium. The resulting increase in leverage raises equilibrium credit risk and offsets the direct effect of improved recovery values on lenders' expected losses.

To better understand this mechanism, Figure 10 plots debt prices and credit spreads as functions of the debt-to-capital ratio for different recovery rates. Holding productivity, capital, and debt fixed, higher recovery values increase debt prices and lower borrowing spreads because lenders expect higher repayment conditional on default. At the same time, Panel B shows that credit spreads remain increasing in leverage for all recovery rates. Importantly, the sensitivity of spreads to leverage becomes substantially flatter when recovery values are high. As a result, firms optimally choose higher leverage positions because the marginal cost of borrowing rises more gradually with debt issuance. The equilibrium increase in credit demand therefore dominates the outward shift in credit supply, generating higher average spreads and default rates despite improved recoverability. The counterfactual exercise in Section 6 can be interpreted as moving from the economy with recovery rate $\gamma = 0.75$ to the economy with $\gamma = 0.45$, where the steeper spread schedule associated with lower recovery values imposes tighter borrowing constraints on firms.

[**Insert Figure 9 Here**]

[**Insert Figure 10 Here**]

Figure 11 presents the main quantitative counterfactual exercise. We vary the recovery rate while holding all remaining model parameters fixed at either their externally calibrated values or their baseline SMM estimates from Section 4. The vertical red lines indicate the equilibrium outcomes associated with the baseline estimated recovery rate.

The counterfactual results show that higher recovery values lead to sizable improvements in aggregate economic outcomes. Aggregate output increases monotonically with the recovery rate and rises by more than 1% as the recovery rate increases from 10% to 100%. Higher recovery values relax financing constraints, improve firms' borrowing capacity, and support greater capital accumulation in equilibrium. The welfare implications are also quantitatively meaningful. Panel A of Figure 11 reports consumption-equivalent welfare gains, defined as the permanent percentage increase in consumption required to make the representative household indifferent between the baseline economy and the counterfactual economy. Welfare increases substantially as recovery values rise.

Panel C shows that aggregate debt issuance increases by approximately 8% as the recovery rate rises from 10% to 100%, indicating that improved collateral recoverability significantly expands equilibrium credit allocation. To further interpret the aggregate implications of financial frictions, we map the model economy into a prototype wedge framework following Chari et al. (2007).[4] Within this representation, changes in financing conditions induced by recovery values can be interpreted as changes in equilibrium wedges. Panel D of Figure 11 shows that the investment wedge declines substantially as the recovery rate increases, consistent with lower distortions in firms' investment decisions. Overall, the results suggest that higher recovery values reduce financing distortions, expand credit allocation, and generate economically meaningful gains in aggregate output and welfare.

[4] Appendix A.3 provides details of the prototype economy and the construction of efficiency and investment wedges.

[**Insert Figure 11 Here**]

5.2 Mechanism and Heterogeneous Firm Responses

This subsection examines the economic mechanisms underlying the aggregate effects of recovery values and studies how firms with different productivity levels respond to changes in financing conditions. Figure 12 reports the percentage changes in the conditional averages of the output-to-capital ratio and newly issued debt-to-capital ratio across firms with low, medium, and high productivity. The debt-to-capital ratio increases for firms at all productivity levels as the recovery rate rises, indicating that improved collateral recoverability relaxes financing constraints throughout the economy. Lower borrowing costs and flatter spread schedules make debt financing more attractive, allowing firms to increase leverage and expand capital accumulation.

The effects on production, however, differ across firms. For low-productivity firms, the output-to-capital ratio initially rises as recovery values increase because previously constrained firms gain access to external financing and expand production. For medium- and high-productivity firms, the output-to-capital ratio declines as recovery values rise. These firms respond strongly to improved borrowing conditions by substantially increasing debt issuance and capital accumulation. Since capital grows faster than output in equilibrium, average output relative to capital declines even though total production increases. At the same time, higher leverage and rising equilibrium wages increase firms' default incentives, leading equilibrium default rates to rise across productivity groups, as shown in Figure 13. Because defaulted capital is partially recovered by lenders and ultimately transferred back to households through the resource constraint, the increase in aggregate capital accumulation exceeds the increase in effective production efficiency for many firms.

Figure 14 further decomposes the aggregate changes in output and debt by productivity group. The increase in aggregate borrowing is broad-based, with firms at all productivity levels issuing more debt as recovery values rise. High-productivity firms exhibit the strongest response and account for a disproportionate share of the increase in aggregate debt and capital accumulation. In contrast, changes in aggregate output are more unevenly distributed across firms. Output produced by low-productivity firms declines overall because the increase in equilibrium leverage and default risk outweighs the production gains among surviving low-productivity firms. As a result, the overall increase in aggregate output is driven primarily by medium- and high-productivity firms, which are better positioned to expand production when financing constraints are relaxed.

Taken together, these results show that higher recovery values improve equilibrium credit allocation by relaxing financing constraints and reducing the sensitivity of borrowing spreads to leverage. Firms respond by increasing debt issuance and capital accumulation, with the strongest responses concentrated among more productive firms. The expansion in credit demand exceeds the increase in effective credit supply, leading equilibrium spreads and default rates to rise despite improved recoverability. Through these heterogeneous financing responses, changes in recovery values generate economically meaningful effects on aggregate output, welfare, and investment distortions.

[**Insert Figure 12 Here**]

[**Insert Figure 13 Here**]

[**Insert Figure 14 Here**]

6 Intangible Capital, Recovery Values, and Aggregate Outcomes

In this section, we examine how the inclusion of intangible capital affects estimated recovery values and the resulting aggregate implications for credit allocation and welfare. To do so, we re-estimate the model using an alternative set of empirical moments constructed with total capital rather than physical capital alone. The targeted micro moments consist of the variance-covariance matrix of profits, total investment, and debt issuance, where all variables are scaled by firms' total capital stocks. Following Peters and Taylor (2017), total capital is defined as the sum of physical and intangible capital, while total investment includes both physical and intangible investment expenditures.

In the baseline estimation, firms' capital stocks are measured using physical capital only, and the targeted moments are constructed from physical investment. However, the empirical evidence in Section 2.2 suggests that firms with greater intangible intensity tend to face different financing conditions, consistent with lower collateral recoverability. This motivates a broader interpretation of productive capital that explicitly incorporates intangible assets. The key question in this exercise is whether the model-implied recovery value declines once intangible capital is included in firms' balance sheets. A lower estimated recovery rate would imply that intangible assets are less pledgeable and have lower liquidation value than physical capital. The exercise therefore allows the model to quantify how rising intangible intensity may affect equilibrium borrowing conditions, financial frictions, and aggregate outcomes through the recovery-rate channel.

Following the estimation procedure in Section 4, we re-estimate the model parameters using simulated method of moments by targeting the moments reported in Table 8.

The targeted micro moments consist of the variance-covariance matrix of profits, total investment rates, and debt issuance, where investment and capital now include both physical and intangible components. We additionally target the average credit spread and average default rate as macro moments. Table 9 reports the resulting SMM parameter estimates and standard errors.

The estimated recovery rate declines substantially once intangible capital is incorporated into the definition of firms' productive assets. The model-implied recovery rate falls to 0.4676, approximately 37% below the baseline estimate of 0.7404 obtained using physical capital only. Quantitatively, this estimate implies that lenders recover roughly 47% of the after-tax undepreciated value of total capital in default states. The lower estimated recovery value is consistent with the idea that a large fraction of intangible capital is difficult to liquidate or pledge as collateral. The estimate is also closer to the empirical recovery values documented in the corporate finance literature. More broadly, the results suggest that the composition of firms' capital stocks materially affects equilibrium borrowing capacity and financing conditions through the recoverability channel.

Table 10 evaluates the model fit under the total-capital specification. Overall, the model matches the empirical moments more closely when intangible capital is incorporated. In particular, the volatility of profits in the data becomes substantially smaller once R&D and SG&A expenditures are treated as investment rather than operating expenses. The model also better matches the correlation between profits and total investment as well as the stronger empirical relationship between total investment and debt issuance. Average spreads and default rates are likewise fit more accurately under the broader capital specification.

To quantify the aggregate implications of rising intangible intensity, we conduct a counterfactual exercise in which the recovery rate is set equal to the model-implied estimate obtained under the total-capital specification, while all remaining parameters are fixed at their baseline values. This experiment isolates the effects of lower collateral recoverability associated with greater reliance on intangible capital. Table 11 summarizes the results. Lowering the recovery rate from 0.7404 to 0.4676 reduces aggregate welfare by 0.10% and aggregate output by 0.37%. At the same time, the investment wedge increases by 8.05%, indicating tighter financing conditions and larger distortions in capital accumulation. Interestingly, equilibrium credit spreads decline by 19.96% and default rates decline by 54.22%, reflecting lower equilibrium leverage and reduced borrowing activity when recovery values are low. Overall, the counterfactual results suggest that the rise of intangible capital may reduce aggregate output and welfare through its effects on collateral recoverability and equilibrium credit allocation, even as equilibrium credit risk becomes lower.

[Insert Table 8 Here]

[Insert Table 9 Here]

[Insert Table 10 Here]

[Insert Table 11 Here]

7 Conclusion

This paper studies how recovery rates shape firms' financing and investment decisions and quantifies the aggregate implications of recovery-driven financial frictions. We develop a quantitative heterogeneous-firm general equilibrium model in which recovery rates play a central role in equilibrium debt pricing and credit allocation, and we structurally estimate the model using micro and macro moments constructed from U.S. public firms. The baseline SMM estimate implies a recovery rate of approximately 74%. Counterfactual exercises show that lower recovery values tighten financing conditions, reduce equilibrium credit allocation, and lower aggregate capital accumulation, leading to economically meaningful declines in aggregate output and welfare. At the same time, lower recovery values reduce equilibrium leverage and borrowing activity, generating lower average default rates and credit spreads. The model therefore highlights an important equilibrium tradeoff between real economic activity and measured credit risk. Importantly, these equilibrium patterns are consistent with the empirical relationships documented in the firm-level data.

The paper further studies the role of intangible capital by broadening the empirical definition of productive capital to include intangible assets. Under this specification, the estimated recovery rate declines to approximately 46%, nearly 37% below the baseline estimate obtained using physical capital only. The lower recovery value is consistent with the idea that intangible assets are less pledgeable and harder to liquidate in default states. Quantitative counterfactuals suggest that the rise of intangible capital can generate nontrivial reductions in aggregate output and welfare through the recovery-value channel, even though equilibrium credit spreads and default rates decline as firms optimally reduce leverage.

More broadly, the results emphasize the importance of recovery values for understanding equilibrium credit allocation, financing constraints, and aggregate production. The analysis nevertheless abstracts from several potentially important dimensions. The empirical exercises focus on publicly listed firms, which are relatively large and mature firms but account for a substantial share of debt financing and capital investment in the

U.S. economy. The framework also abstracts from mechanisms through which intangible capital may affect productivity growth, depreciation dynamics, or returns to scale. In practice, intangible assets such as organizational capital, brands, and data capital may generate spillovers, affect markups, or alter firms' production technologies beyond their role in collateral recoverability. Measurement issues related to intangible investment and the construction of appropriate deflators also remain important challenges.

Several extensions provide promising directions for future research. One natural extension is to estimate industry-specific recovery values and study how sectoral composition changes affect aggregate credit allocation and macroeconomic outcomes. Another direction is to incorporate richer debt structures. For example, Kermani and Ma (2020) distinguish between asset-based and cash-flow-based debt contracts, implying that firms' borrowing capacity may depend not only on collateral recoverability but also on expected future cash flows. Extending the framework to incorporate multiple forms of debt financing could provide additional insights into how financial structure interacts with recovery rates and the growing importance of intangible capital in modern economies.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

AI-assisted tools, including ChatGPT and Grammarly, were used to edit the manuscript for clarity and language. These tools did not generate scientific content or contribute to data analysis, interpretation, or conclusions. All content was reviewed and verified by the authors, who retain full responsibility for the manuscript.

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Tables and Figures

Figures

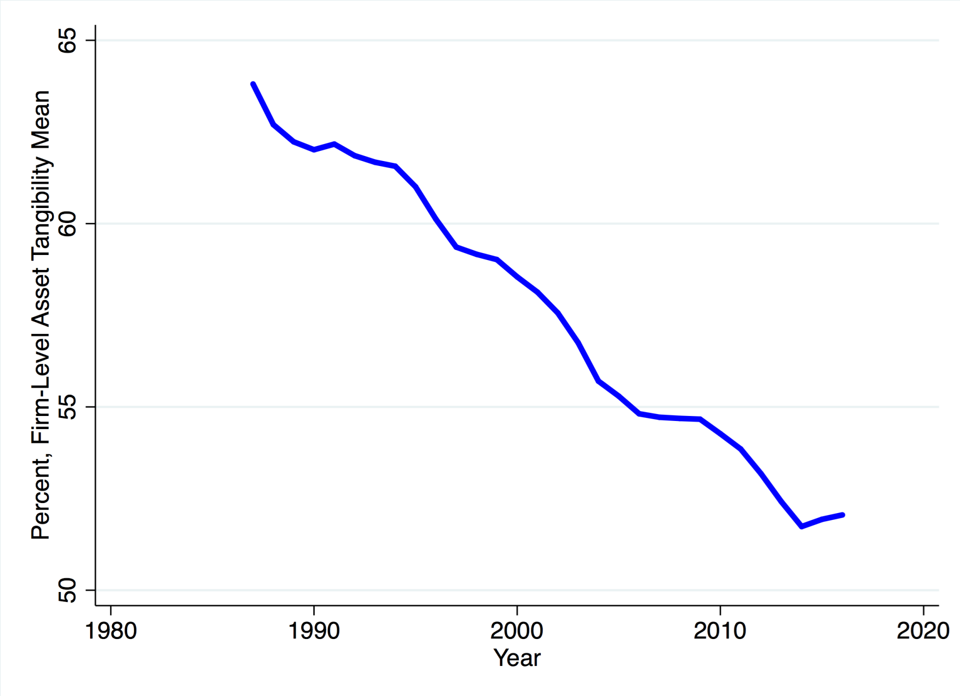
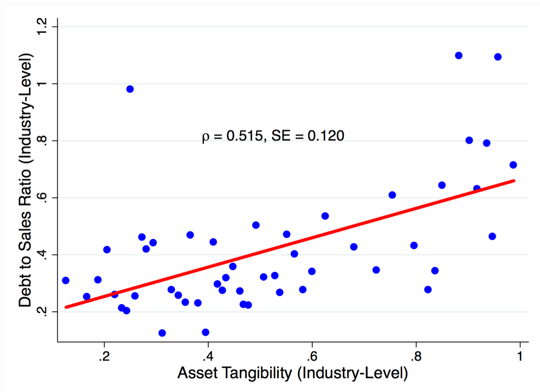
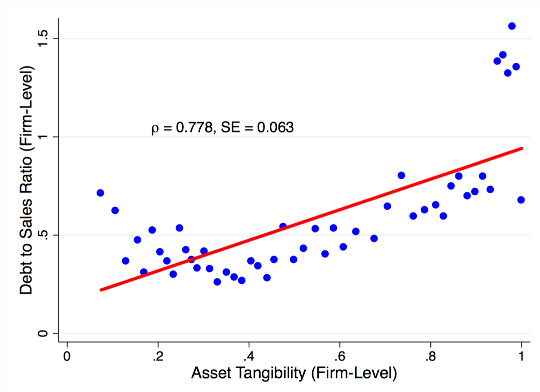


Figure 1: Physical Capital Share is Declining

Notes: The figures plots the annual average asset tangibility for firms in my CRSP/Compustat merged panel for period 1987-2016. Asset tangibility is measured as physical capital over sum of physical capital and off-balance sheet intangible capital. Firm-level intangible capital is taken from Peters and Taylor (2017).



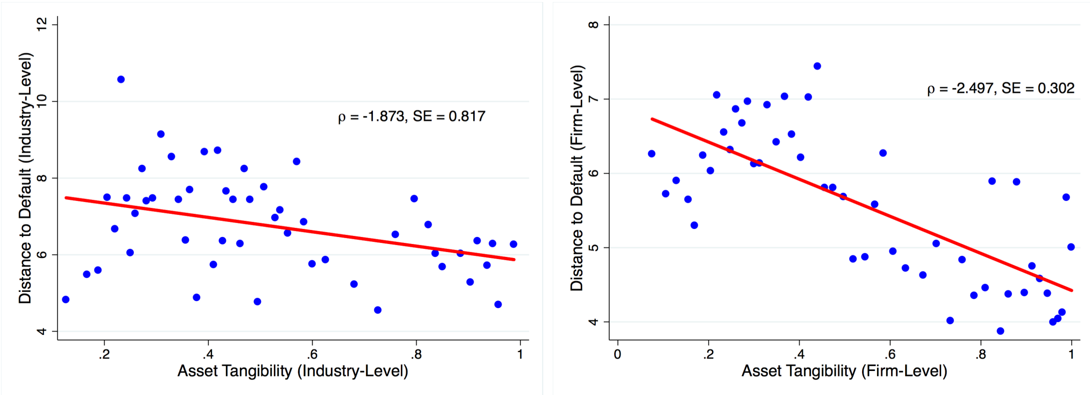
Panel A. Industry-Level



Panel B. Firm-Level

Figure 2: Debt-to-sales Ratio with Asset Tangibility in Long-run (Binned Scatterplots)

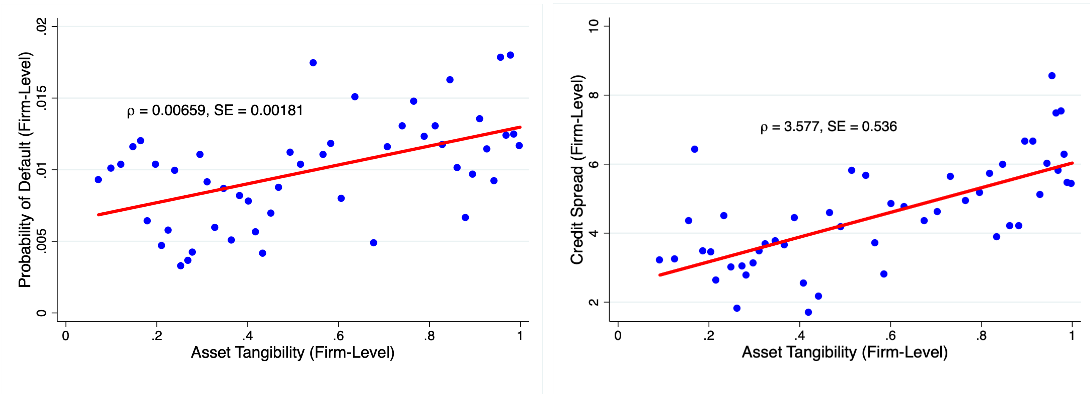
Notes: Figures present cross-sectional results by averaging observations in my CRSP/Compustat merged panel covering 1987-2016. Asset tangibility is measured as physical capital over sum of physical capital and off-balance sheet intangible capital. Firm-level intangible capital is taken from Peters and Taylor (2017). Asset tangibility is positively correlated with debt-to-sales ratio. Panel A: regression coefficient $\rho = 0.515$, $SE = 0.120$, $N^{\text{industry}} = 209$. Panel B: regression coefficient $\rho = 0.778$, $SE = 0.063$, $N^{\text{firm}} = 1142$.



Panel A. Industry-Level Panel B. Firm-Level

Figure 3: Distance to Default with Asset Tangibility in Long-run (Binned Scatterplots)

Notes: Figures present cross-sectional results by averaging observations in my CRSP/Compustat merged panel covering 1987-2016. Asset tangibility is measured as physical capital over sum of physical capital and off-balance sheet intangible capital. Firm-level intangible capital is taken from Peters and Taylor (2017). Asset tangibility is negatively correlated with distance to default. Panel A: regression coefficient $\rho = -1.873$, $SE = 0.817$, $N^{\text{industry}} = 209$. Panel B: regression coefficient $\rho = -2.497$, $SE = 0.302$, $N^{\text{firm}} = 1142$.



Panel A. Probability of Default Panel B. Credit Spread

Figure 4: Credit Risks with Asset Tangibility at Firm-Level (Binned Scatterplots)

Notes: Figures present cross-sectional results by averaging observations in my CRSP/Compustat merged panel covering 2002-2016. Asset tangibility is measured as physical capital over sum of physical capital and off-balance sheet intangible capital. Firm-level intangible capital is taken from Peters and Taylor (2017). Asset tangibility is negatively correlated with distance to default. Probability of Default is taken from NUS-CRI credit risk assessments and credit spread is computed using FISD-TRACE data.

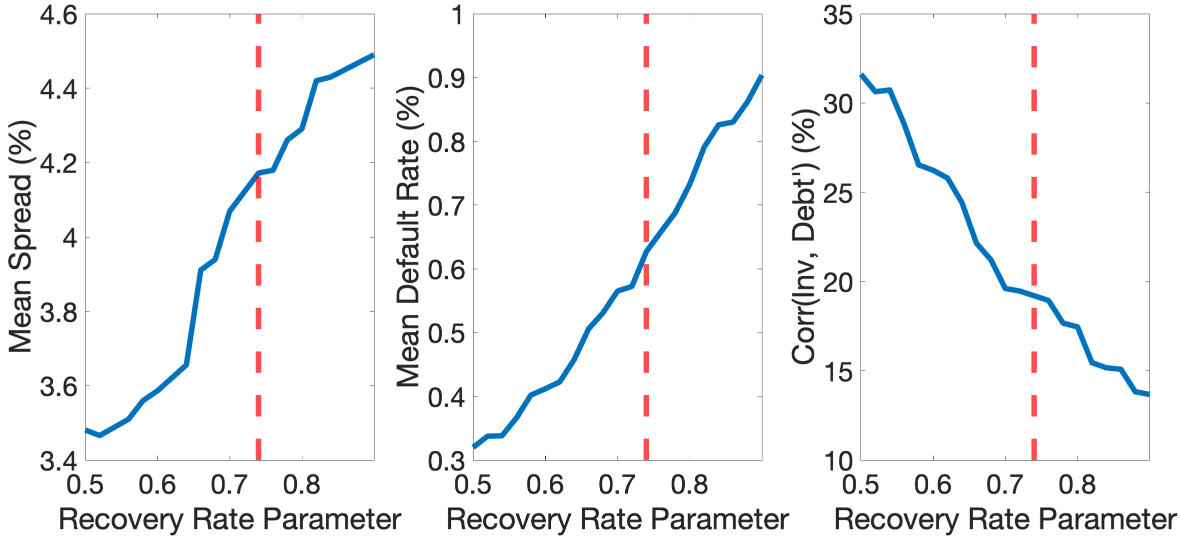


Figure 5: Sensitivity of moments to the recovery rate γ

Notes: In this figure, I set all estimated parameters $(\phi, \gamma, \rho_z, \sigma_z, \eta_1)$ at their SMM estimate in Section 4.4. I then vary γ from 0.5 to 0.9. For each value of γ that I choose, I solve the model, simulate the data, and compute the mean spread, the mean default rate, and the correlation between investment and debt issuance. The red vertical line corresponds to the SMM estimate of γ.

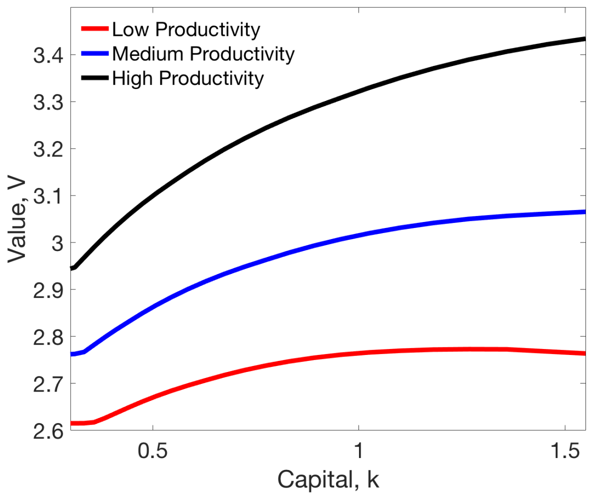


Figure 6: Firm Value

Notes: The figure plots the value function as a function of firm capital k for the estimated model. All lines hold fixed the value of micro TFP z, and firm's debt to capital ratio b/k. The three lines reflect different realizations of micro TFP z, with high productivity (black line), medium productivity (blue line), and low productivity (red lines).

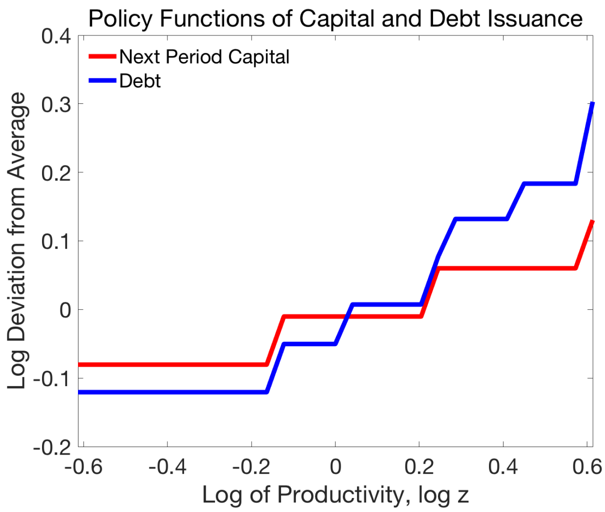
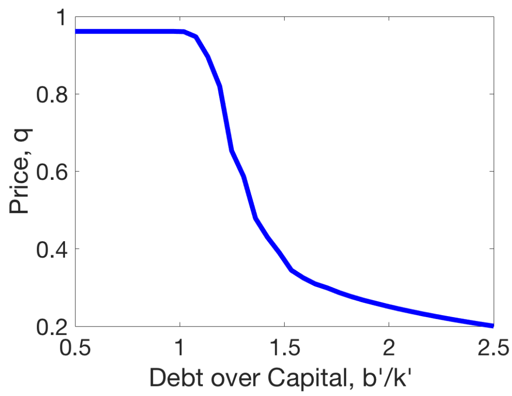
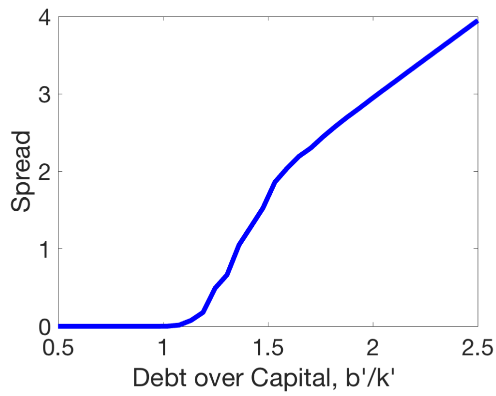


Figure 7: Policy Function

Notes: The figure plots the policy functions as functions of log of micro TFP z for the estimated model. All lines hold fixed the values of capital k and debt b at the means in ergodic distribution. The red line reflects the log deviation of next period capital from the average capital stock, and the blue line reflects the log deviation of debt issuance from the average debt level.



Panel A. Debt Pricing



Panel B. Spread

Figure 8: Price of Debt

Notes: The figure plots the debt price and spread as functions of debt-to-capital ratio b'/k' for the estimated model. All lines hold fixed the values of micro TFP z and capital k' at the averages in ergodic distribution.

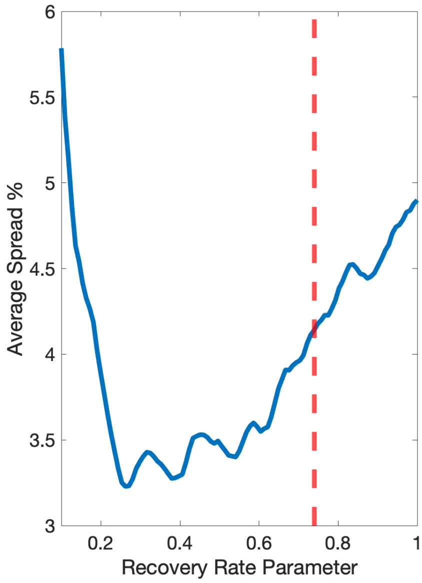
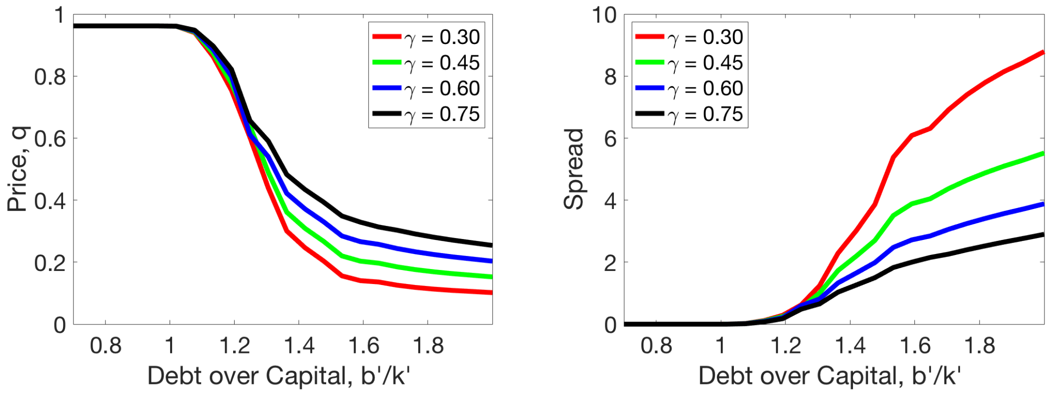


Figure 9: Average Spread and Default Rate

Notes: The figure plots the average spread and default rate for the model economy with different recovery rates. In this figure, I set all estimated parameters $(\phi, \gamma, \rho_z, \sigma_z, \eta_1)$ at their SMM estimate in Section 4.4. I then vary γ from 0.1 to 1.0. For each value of γ that I choose, I solve the model, simulate the data, and compute the average spread and average default rate. The red vertical line corresponds to the SMM estimate of γ.

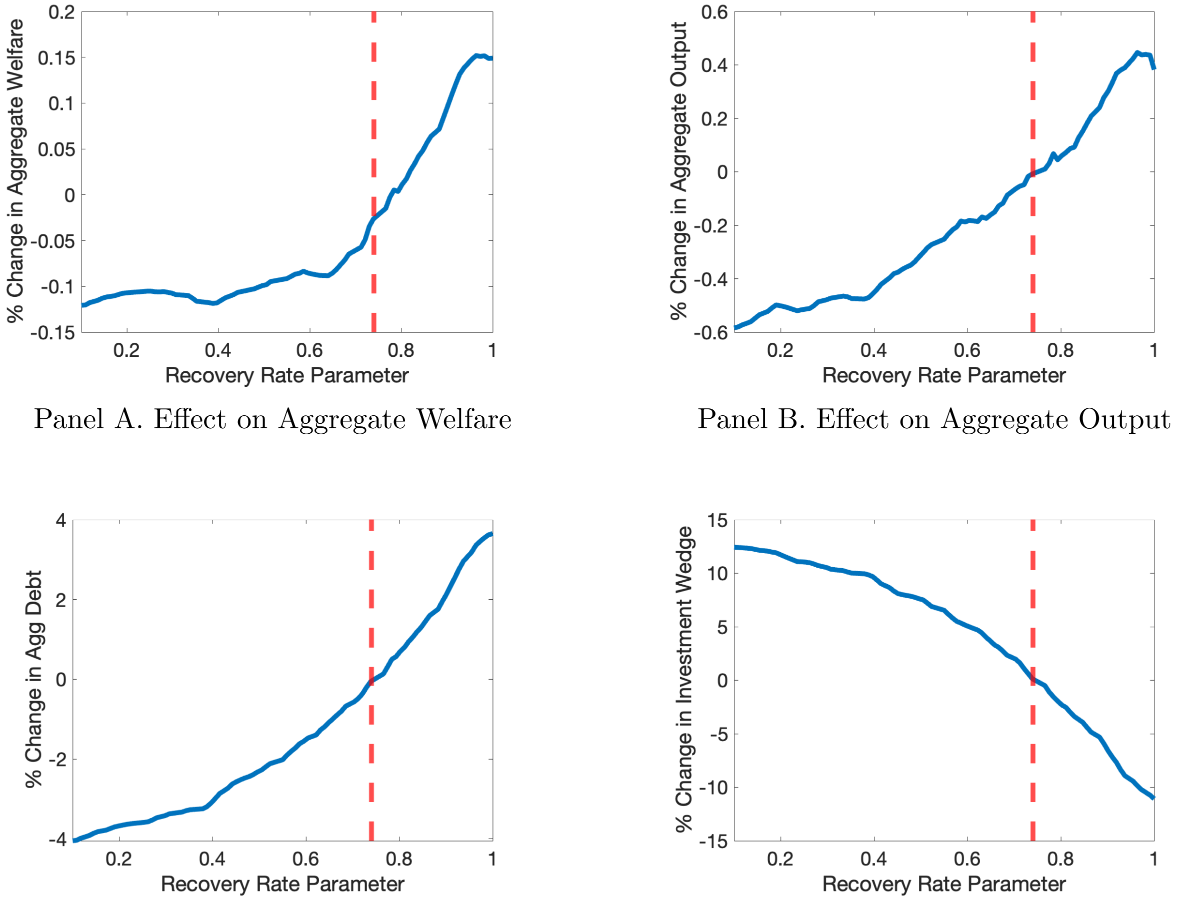


Panel A. Debt Pricing

Panel B. Spread

Figure 10: Price of Debt with Different Recovery Rates

Notes: The figure plots the debt price and spread as functions of debt-to-capital ratio b'/k' for the estimated model. All lines hold fixed the values of micro TFP z and capital k' at the averages in ergodic distribution. The four lines reflect debt price and spread for different values of the recovery rate, with recovery rate equals to 0.30 (red line), 0.45 (green line), 0.6 (blue line), and 0.75 (black lines).



Panel A. Effect on Aggregate Welfare

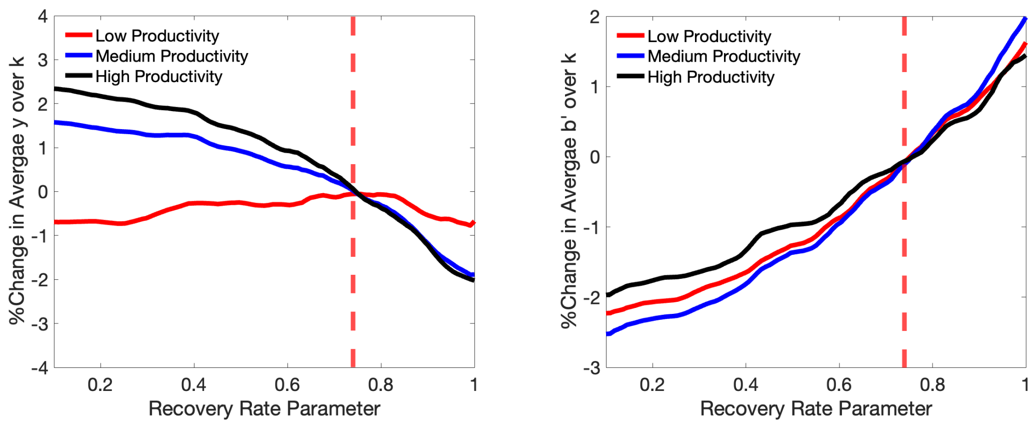
Panel B. Effect on Aggregate Output

Panel C. Effect on Aggregate Debt

Panel D. Change in Investment Wedge

Figure 11: Aggregate Impacts of the Recovery Rate

Notes: The figure plots the changes in aggregate consumption-equivalent welfare, aggregate output, aggregate debt issued and capital investment wedge in counterfactual economies with different recovery rates referring to the values in my Baseline economy with the SMM estimated recovery rate. The red vertical line corresponds to the SMM estimate of γ.



Panel A. Conditional Average of y/k

Panel B. Conditional Average of b'/k

Figure 12: Average y/k and b'/k at Different Productivity

Notes: The figure plots the changes in the average output to capital ratio and debt issuance to capital ratio for firms with different productivity levels. The conditional means are calculated by using the ergodic distribution. The red vertical line corresponds to the SMM estimate of recovery rate γ.

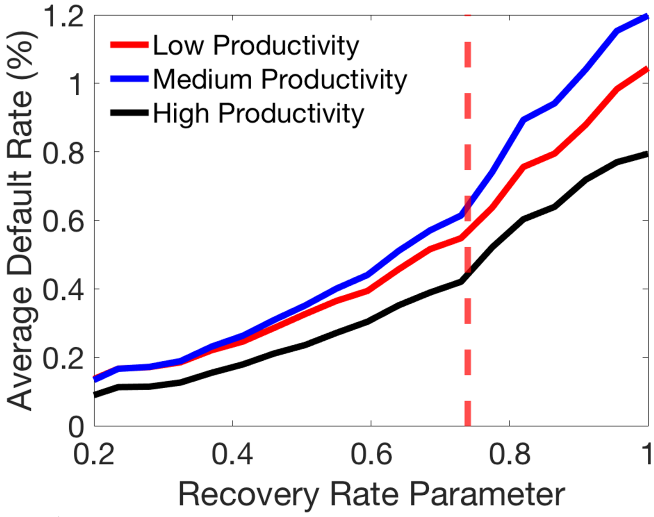
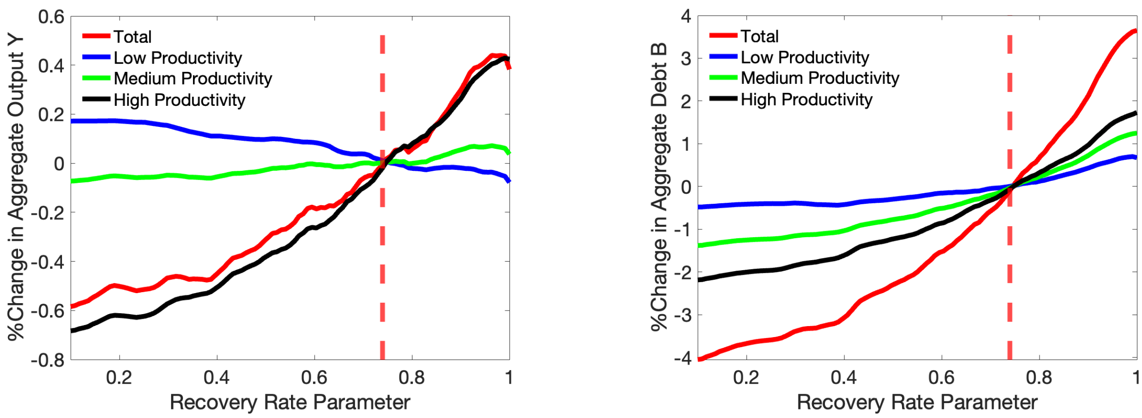


Figure 13: Average Default Rate of Firms at Different Productivity

Notes: The figure plots the average default rate for firms with different productivity levels. The red vertical line corresponds to the SMM estimate of γ.



Panel A. Aggregate Output

Panel B. Aggregate Debt

Figure 14: Changes in Aggregate Variables Contributed by Firms at Different Productivity

Notes: The figure plots the changes in aggregate output and debt contributed by firms with different productivity levels. The red vertical line corresponds to the SMM estimate of γ.

Tables

Table 1: Summary Statistics

Variable	Mean	Median	Std. Dev.	Firm-Years
Sales (millions)	7,282.337	2,277	19,363.52	12,161
Physical capital stock (millions)	2,679.441	707.974	8,159.771	12,161
Intangible capital stock (millions)	2,202.775	509.6265	6,433.443	12,161
Total debt (millions)	1,926.95	658.341	3,950.606	12,159
Physical investment	0.1114	0.0767	0.1279	12,161
Intangible investment	0.1147	0.1056	0.0971	12,161
Asset tangibility	0.5538	0.5246	0.2858	12,161
Debt-to-sales ratio	1.7747	0.3061	86.1961	12,159
Distance to default	6.4728	5.6949	4.6526	11,889

Notes: The table reports basic descriptive statistics for several variables drawn from my CRSP-Compustat merged panel of firms covering 1987-2016 at the firm-year level before winsorization. The final column reports the number of non-missing firm-years in my sample for the indicated variable. Total capital stock is used as denominator to construct physical investment and intangible investment.

Table 2: Debt-to-Sales Ratio with Asset Tangibility

	Debt-to-Sales Ratio					
	Industry-Level			Firm-Level		
	(1)	(2)	(3)	(4)	(5)	(6)
Asset Tangibility	0.609***	0.360**	0.399**	0.716***	0.259***	0.294***
	(0.088)	(0.123)	(0.127)	(0.048)	(0.071)	(0.088)
Cluster	Industry	Industry	Industry	Firm	Firm	Firm
Year FE	Y	N	Y	Y	N	Y
Industry FE	N	Y	Y	N	N	N
Firm FE	N	N	N	N	Y	Y
N	4214	4209	4209	12159	12045	12045
R^2	0.176	0.622	0.641	0.157	0.815	0.824

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Distance to Default with Asset Tangibility

	Distance to Default					
	Industry-Level			Firm-Level		
	(1)	(2)	(3)	(4)	(5)	(6)
Asset Tangibility	-1.829***	-3.899***	-1.441*	-2.408***	-3.941***	-0.614
	(0.496)	(0.726)	(0.699)	(0.396)	(0.709)	(0.657)
Cluster	Industry	Industry	Industry	Firm	Firm	Firm
Year FE	Y	N	Y	Y	N	Y
Industry FE	N	Y	Y	N	N	N
Firm FE	N	N	N	N	Y	Y
N	4162	4157	4157	11889	11774	11774
R^2	0.307	0.327	0.597	0.226	0.545	0.713

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Externally Fixed Parameters

	Parameter	Value	Explanation	Source
1	r	0.04	Risk-free rate	Annual solution
2	δ	0.12	Physical capital depreciation rate	Falato et al. (2022)
3	ν	0.50	Labor revenue elasticity	Bloom et al. (2018)
4	α	0.25	Physical revenue elasticity	Bloom et al. (2018)
5	τ	0.20	Corporate income tax	Effective corporate tax rates
6	ψ	2.0	Leisure preference	Households spend one-third of time working

Notes: The table reports the parameter symbol, numerical value, description, and source information for each externally fixed parameter.

Table 5: Target Moments for SMM Estimation

Micro Moments			
	Moment	Value	SE
1	Var(Profit)	0.175487	0.0136
2	Cov(Profit, Phys Inv)	0.006417	0.0010
3	Cov(Profit, Debt′)	0.035982	0.0147
4	Var(Phys Inv)	0.008279	0.00046
5	Cov(Phys Inv, Debt′)	0.016254	0.0026
6	Var(Debt′)	1.03081	0.1162
Macro Moments			
	Moment	Value	SE
1	Average Spread	0.0287	0.0184
2	Average Default	0.0035	0.0031

Notes: The micro moments were computed on a sample from CRSP-Compustat merged annual data from 2001-2016, with 7324 firm-years spanning 1022 firms. The reported standard errors for the micro moments are computed using firm-level clustering. An prime symbol (′) indicates future values. Profit, physical capital investment, debt are expressed relative to firm physical capital stocks. For the macro moments, the mean spread and mean default rate across firms are taken from Bordalo et al. (2026).

Table 6: Estimated Parameters

	Parameter	Explanation	Value	SE
1	ϕ	Cost of adjustment for capital	4.0596	0.3208
2	γ	Recovery rate of capital	0.7404	0.2496
3	ρ_z	Micro TFP persistence	0.7560	0.0991
4	σ_z	Micro TFP shock sd	0.1606	0.0299
5	η_1	Linear cost of equity finance	0.0674	0.0186

Notes: The table reports point estimates and standard errors for each of the parameters in my SMM estimation. The moment Jacobian is computed numerically. In the SMM estimation, the weighting matrix is the inverse of the data moment covariance matrix.

Table 7: Model vs Data Moments

	Micro Moments		
	Moment	Data	Model
1	Std Dev(Profit)	0.4188	0.1387
2	Corr(Profit, Phys Inv)	0.1684	0.5768
3	Corr(Profit, Debt′)	0.0846	0.5563
4	Std Dev(Phys Inv)	0.0909	0.0587
5	Corr(Phys Inv, Debt′)	0.1759	0.1698
6	Std Dev(Debt′)	1.0153	0.1871
	Macro Moments		
	Moment	Data	Model
1	Average Spread	0.0287	0.0429
2	Average Default	0.0035	0.0064

Notes: The data column reports the empirical values of the target moments for my SMM exercise. The model column reports the target moments with my estimated parameters from the baseline model. The empirical micro moments are computed on a sample from CRSP-Compustat merged annual data from 2001-2016, with 7324 firm-years spanning 1022 firms. For the empirical macro moments, the mean spread and mean default rate across firms are taken from Bordalo et al. (2026). The model moments are based on a simulation of 5,000 firms for 250 years. An prime symbol (′) indicates future values. Profit, physical capital investment, debt are expressed relative to firm physical capital stocks. For the model macro moments, the mean spread is the average across years of the mean spread across firms with non-zero borrowing, the mean default rate is the average across years of the mean default rate across firms with non-zero borrowing.

Table 8: Target Moments for SMM Estimation (Total Capital)

	Micro Moments		
	Moment	Value	SE
1	Var(Profit)	0.00911	0.00041
2	Cov(Profit, Total Inv)	0.00173	0.00010
3	Cov(Profit, Debt′)	0.00049	0.00051
4	Var(Total Inv)	0.00289	0.00012
5	Cov(Total Inv, Debt′)	0.00247	0.00027
6	Var(Debt′)	0.04320	0.00260

	Macro Moments		
	Moment	Value	SE
1	Average Spread	0.0287	0.0184
2	Average Default	0.0035	0.0031

Notes: The micro moments were computed on a sample from CRSP-Compustat merged annual data from 2001-2016, with 7324 firm-years spanning 1022 firms. The reported standard errors for the micro moments are computed using firm-level clustering. An prime symbol (′) indicates future values. Profit, total capital investment, debt are expressed relative to firm total capital stocks. Total capital investment is the sum of physical, knowledge and organization investment. Total capital is the sum of physical, knowledge and organization capital. For the macro moments, the mean spread and mean default rate across firms are taken from Bordalo et al. (2026).

Table 9: Estimated Parameters (Total Capital)

	Parameter	Explanation	Value	SE
1	ϕ	Cost of adjustment for capital	4.5044	0.2474
2	γ	Recovery rate of capital	0.4676	0.0296
3	ρ_z	Micro TFP persistence	0.8251	0.0056
4	σ_z	Micro TFP shock sd	0.0865	0.0052
5	η_1	Linear cost of equity finance	0.0584	0.0020

Notes: The table reports point estimates and standard errors for each of the parameters in my SMM estimation. The moment Jacobian is computed numerically. In the SMM estimation, the weighting matrix is the inverse of the moment covariance matrix.

Table 10: Model vs Data Moments (Total Capital)

Micro Moments			
	Moment	Data	Model
1	Std Dev(Profit)	0.09545	0.08434
2	Corr(Profit, Total Inv)	0.3373	0.4146
3	Corr(Profit, Debt′)	0.0245	0.6708
4	Std Dev(Total Inv)	0.05374	0.04552
5	Corr(Total Inv, Debt′)	0.2213	0.3655
6	Std Dev(Debt′)	0.20785	0.12603
Macro Moments			
	Moment	Data	Model
1	Average Spread	0.0287	0.0353
2	Average Default	0.0035	0.0039

Notes: The data column reports the empirical values of the target moments for my SMM exercise. The model column reports the target moments at my estimated parameters from the model targeting moments constructed using total capital. The empirical micro moments were computed on a sample from CRSP-Compustat merged annual data from 2001-2016, with 7324 firm-years spanning 1022 firms. For the empirical macro moments, the mean spread and mean default rate across firms are taken from Bordalo et al. (2026). The model moments are based on a simulation of 5,000 firms for 250 years. An prime symbol (′) indicates future values. Profit, total capital investment, debt are expressed relative to firm total capital stocks. For the model macro moments, the mean spread is the average across years of the mean spread across firms with non-zero borrowing, the mean default rate is the average across years of the mean default rate across firms with non-zero borrowing.

Table 11: Counterfactual with Total Capital Implied Recovery Rate

	Aggregate Moments	Change Relative to Baseline
1	Aggregate Welfare	-0.1055%
2	Aggregate Output	-0.3691%
3	Capital Investment Wedge	8.0533%
4	Average Spread	-19.9620%
5	Average Default Rate	-54.2270%

Notes: This table reports the percentage changes in aggregate consumption-equivalent welfare, aggregate output, capital investment wedge, average spread and average default rate when the recovery rate is fixed at the estimated value when intangible capital is taken into consideration.

Appendix

A Model

A.1 Solving the Model

A solution to the model reflects a set of firm-level policies k', b', df and values V, V_{ND}, V_D together with a debt price schedule q, an equilibrium wage rate W, and a real interest rate r. Because the model has no closed-form solution, we solve the model using numerical methods and dynamic programming.

The state space for (z, k, b) is discretized. We transform the AR(1) micro TFP process into a discrete-state Markov chain using the method in Tauchen (1986), letting z to have $n_z = 31$ points. The numbers of points for capital k and debt b are set to be the same as $n_k = n_b = 100$. The supports are set such that the density at the endpoints is close to zero in the stationary distribution.

We employ the "inner loop/outer loop" approach to solve this quantitative dynamic general equilibrium model. The numerical solution proceeds in two steps. First, we make an initial guess of the wage rate W and calculate an implied aggregate consumption value consistent with the optimality condition of the household's problem. Taking the wage rate as given, we solve for a firm's default rule df and compute the implied debt price schedule q according to the lenders' zero-profit condition. Second, we solve the Bellman equations for V, V_{ND}, and V_D using policy function iteration. If the value functions and policy functions converge, then the inner loop is complete. Otherwise, we update the policy functions and repeat the process. After completing the inner loop, we use the stationary distribution to calculate the aggregate consumption, which clears the goods market. If the difference between this aggregate consumption and the initial implied aggregate consumption is smaller than the tolerance we set, the outer loop is complete, and the model is solved.

A.2 Simulating the Model

After the model is solved, we unconditionally simulate the model by drawing exogenous uniform random shocks and combine this with the transition matrix for micro TFP to simulate the AR(1) process of firm-level productivity. We simulate the model for a large number of firms with $N_{firm} = 5000$ for periods $T_{sim} = 275$ using the simulated micro TFP and discard the first 25 periods to remove the influence of initial conditions. Then this simulated panel is used for computing moments within my SMM estimation algorithm.

A.3 Investment Wedge and Efficiency Wedge

To study the aggregate impact of financial frictions, we map my Baseline economy to a prototype economy with efficiency wedge and investment wedge as suggested in Chari et al. (2007). By doing this, we can interpret changes in financial frictions in my Baseline economy as changes in wedges in the prototype economy. Suppose a representative firm with macro TFP A combines capital K and labor N as inputs to produce output Y using a Cobb-Douglas production function

$$Y = AK^{\alpha}N^{\nu}, \quad \alpha + \nu < 1,$$

it solves a static optimization problem

$$\pi = (1 - \tau_Y)Y - WN - (1 + \tau_K)RK$$

where τ_Y is the efficiency wedge and τ_K is the investment wedge. These wedges can be interpreted as taxes that distort the economy and used for understanding the impacts of financial frictions. First order conditions with respect to K and N are

$$(1 - \tau_Y)A\alpha K^{\alpha-1}N^{\nu} - (1 + \tau_K)R = 0,$$
$$(1 - \tau_Y)A\nu K^{\alpha}N^{\nu-1} - W = 0.$$

Simplifying these first order conditions, we have

$$\nu\frac{Y}{N} = \frac{W}{1 - \tau_Y}, \quad \alpha\frac{Y}{K} = \frac{(1 + \tau_K)R}{1 - \tau_Y}, \quad \frac{\alpha N}{\nu K} = \frac{(1 + \tau_K)R}{W}$$

$$\tau_Y = 1 - \frac{\psi NC}{\nu Y}, \quad \tau_K = \frac{\alpha\psi NC}{\nu K(r + \delta)} - 1$$

When the recovery rate of capital changes, we can understand the impact of this change in financial frictions on this equivalent economy with efficiency wedge and investment wedge.

B Data Construction and Sample Selection

The firm-level variables used in the empirical analysis of this paper are based on annual CRSP/Compustat merged data. The definition of the variables and sample selection follow standard practices in the literature. ((Hennessy and Whited 2007; Peters and Taylor 2017; Bordalo et al. 2026)).

Variables:

1. Earnings or profits π: equal to GAAP net income, Compustat variable *ib*. The model equivalent is $\pi = (1-\tau)(y - AC(k,i) - Wn) + \tau(rb + \delta k) - \delta k$

2. Physical capital k: measured by the net book value of plants, property, and equipment, Compustat variable *ppent*. The model equivalent is the state variable k.

3. Investment i: equal to the total value of capital expenditures, Compustat variable *capxv*. The model equivalent is the policy variable $i = k' - (1-\delta)k$.

4. Debt b: defined as the sum of total debt, Compustat variable *dltt* + *dlc*. The model equivalent is the state variable b.

5. Sales: Compustat variable *sale*.

6. Distance to default: I follow an iterative procedure based on Gilchrist and Zakrajšek (2012) and Ottonello and Winberry (2020) and mainly use the equations in Blanco and Navarro (2016) and the equation provided in Merton (1974).

$$dd \equiv \frac{log(V/D) + \mu_V T - 0.5\sigma_V^2 T}{\sigma_V \sqrt{T}}$$

where V denotes total value of firm, μ_V the expected return on V, σ_V the volatility on V, D firm's debt, and T the number of days to use for calculating μ_V and σ_V. V needs. I take $T = 252$ since my time horizon for calculating firm's value is 1 year, and 252 trading days in a year. Probability to default PD:

$$PD = \Phi(-dd)$$

where Φ is the CDF of standard normal distribution. To estimate V, I use the following iteration procedure:

- Step I: Set an initial guess of firm value as sum of firm's debt level and equity level at current day t, $V = E + D$. E is measured as firm's stock price times the number of shares outstanding. D is computed as firm's short-term debt plus one-half of long-term from Compustat at quarterly frequency, then the data is linearly interpolated to obtain daily observations.

- Step II: Estimate the mean and standard deviation of return on firm value over a 252-day moving window. The return on firm value is measured as daily log return on assets, $\Delta \log V$.

- Step III: Obtain a new estimate of firm value for every day of the 252-day moving window from the Black-Scholes-Merton option-pricing framework:

$$E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2)$$

where $\delta_1 \equiv \frac{\log(V/D)+(r+0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$ and $\delta_2 \equiv \delta_1 - \sigma_V\sqrt{T}$. r is the daily one-year constant maturity Treasury-yield. Use preferred nonlinear solver for solving equation.

- Step IV: Iterate on Step II and III until we get convergence on firm's value V at each day.

7. Size: measured as the log of total assets, Compustat variable *at*.

8. Knowledge capital, organization capital, and intangible capital: estimated by Peters and Taylor (2017) from 1979 to 2017. Access through Wharton Research Data Services, variables *k_int_know*, *k_int_org* and *k_int_offbs*.

9. Asset Tangibility: defined as physical capital over sum of physical and intangible capital.

Sample Selection: My empirical analysis excludes:

1. Firms in, utilities ($sic \in [49, 50)$) finance, insurance and real estate sectors ($sic \in [60, 67]$) and public administration ($sic \in [91, 97]$).

2. Firms not incorporated in the United States.

3. Firms exists in the data for smaller than 5 years.

4. Firm-year observations with acquisitions (constructed based on Compustat variable *aqc*) larger than 5% of assets.

5. Firm-year observations with book value of assets missing or negative.

6. Firm-year observations with book value of physical capital missing or negative.

7. Firm-year observations with capital expenditure missing or negative.

8. Firm-year observations without credit ratings.

C SMM Estimation

Our SMM estimation exercise in Section 4 involves three steps: (1) moment and covariance matrix calculations, (2) model estimation, and (3) standard error calculation.

C.1 Moment and Covariance Matrix Calculation

Table 5 reports a set of 8 target moments at the micro and macro levels for our SMM estimation exercise. The micro moments are a covariance matrix of the vector

$$X_{it} = (\text{Profit}_{it}, \text{Investment}_{it}, \text{Debt}_{it})'$$

for firm i in fiscal year t from our CRSP/Compustat merged sample. The sample spans 1022 firms and 7324 total observations. To compute the micro moments, we use the following procedure:

- Demean X_{it} by firm and year to obtain $\hat{X}_{it}$.
- Compute the covariance matrix as the mean of $\hat{X}_{it}\hat{X}'_{it}$.
- Apply the standard formula for the clustered covariance of a mean vector to obtain the moment covariance matrix Ω_{Micro}, clustering across firms.

The macro moments are the mean spread and the mean default rate. We use the point estimates and an estimate of the covariance matrix of these two macro moments from Bordalo et al. (2026). Assume that the macro sample length T and the number of micro observations N behave proportionally with $T/N \to \gamma$ for some constant γ as $N \to \infty$. This allows us to rely on asymptotics of the basic form

$$\sqrt{N}(\hat{m} - m) \to_{d,N\to\infty} N(0, \Omega),$$

where $\hat{m}$ is the estimated moment vector (with micro and macro moments) and Ω is the joint moment covariance adjusted for γ.

$$\Omega = \begin{bmatrix} \Omega_{Micro} & 0 \\ 0 & \frac{1}{\gamma}\Omega_{Macro} \end{bmatrix}$$

Table 5 and Table 8 report $\hat{m}$ and standard errors based on the approximating variance from (12).

C.2 Point Estimate Calculation

We compute the point estimates estimates $\hat{\theta}$ for the vector of estimated parameters θ in Table 6 and Table 9 by solving the following standard SMM optimization problem

$$\hat{\theta} = argmin_{\theta}(m(X) - m_S(\theta))'W(m(X) - m_S(\theta))$$

where $m_S(\theta)$ is the model value of the moments given θ computed from simulated data, the weighting matrix W is the inverse of the variance-covariance matrix of data moments $\hat{\Omega}^{-1}$ implying an asymptotically efficient SMM estimator, and $m(X)$ is the empirical moment vector. We employ particle swarm optimization to solve this optimization problem, a stochastic global optimization routine that bears substantial similarity to simulated annealing and genetic algorithms.

In practice, for a given set of parameters, we solve the model using the "inner loop/outer loop" algorithm in Section 3 and obtain the policy functions as functions of state variables. Then we randomly draw the micro TFP shocks and the simulate an artificial panel containing 5,000 independent and identically distributed firms. We simulate each firm for 275 time periods and discard the first 25 observations for each firm. The model-implied moments are generated with this panel of simulated data. We repeat this procedure until the weighted sum of the differences is minimized.

C.3 Standard Error Calculation

Given the ratio between the number of firms N^{sim} in the model simulation used to compute $m_S(\theta)$ and the empirical number of firms N, the SMM estimator's asymptotic covariance matrix Σ follows

$$\sqrt{N}(\hat{\theta} - \theta) \rightarrow_{d,N\rightarrow\infty} N(0, \Sigma),$$

where

$$\Sigma = (1 + \frac{N}{N^{sim}})(\frac{\partial m_S(\theta)}{\partial \theta'}\Omega^{-1}\frac{\partial m_S(\theta)}{\partial \theta})^{-1},$$

Equation (14) yields a feasible formula for Σ after substitution of the estimated covariance matrix $\hat{\Omega}$ and numerical calculation of the moment Jacobian matrix $\frac{\partial m_S(\theta)}{\partial \theta'}$ within the model using forward differentiation from the point estimates $\hat{\theta}$. With these elements in hand, Table 6 and Table 9 report standard errors based on the approximating variance from (13).