The Macro Impact of the Recovery Rate*

Guangzhi Ye†

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Abstract

The recovery rate of capital determines lenders' credit supply, and in equilibrium, affects the demand and total credit amounts. Recent rising intangibles in the US may reduce recovery. I use CRSP/Compustat database to find that firms and industries with higher asset tangibility, a proxy for the recovery rate, issue more debts and have lower distance to default. To understand the aggregates, I build a canonical quantitative general equilibrium heterogeneous firm model and estimate the recovery rate by matching investment and debt covariance, average spread, and average default rate. The simulated method of moments (SMM) estimate of the recovery rate is 74%. The counterfactuals reveal that declines in the recovery rate reduce aggregate output, credit, and welfare by constraining capital accumulation. Tackling intangibles by a broader notion of capital, I estimate a recovery rate of 46% with the same model structure, implying that rising intangibles could cause nontrivial output and welfare losses due to financial frictions.

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†Boston University. Email: gye@bu.edu. Address: 270 Bay State Road, Boston MA 02215.
Web: https://guangzhiye.com

1 Introduction

How do firms' financing decisions interact with capital investment decisions? Do financial frictions matter for the aggregate economy? What are the aggregate implications of the rising intangibility in the US economy? In this paper, I show that firms' asset recovery rate upon default affects decisions of new debt issuance and argue, using a quantitative macro model with capital investment and risky debts, that financial frictions matter for the aggregate economy and the magnitude depends on the recovery rate of capital. According to the estimated structural model, rising intangibles could result in a nontrivial loss of output and welfare via decreased recovery rate, although moderate credit risk at the same time.

Recovery rate is the liquidation value of capital as a fraction of the net book value of its replacement costs. This rate directly affects the spread credit lenders charge for lending to firms and how much they could recover once the firms default. Given the required return of borrowing, firms make optimal decisions in capital investments and debt issuing. So the recovery rate of capital is a crucial object determining credit supply, and in equilibrium, affects the demand and total quantities of credit. It determines the size of financial frictions in the economy.

The recovery rate changes for various reasons. First, the US economy has shifted toward service-based and technology-based industries in recent decades, which has made intangible capital such as accumulated knowledge, patents, software, organizational design, brands, and customer base increasingly important (Corrado, Hulten and Sichel, 2009; Corrado and Hulten, 2010). Some of the intangible capital is identifiable like patents, technologies, brands and usage rights, and they have liquidation values and can be resold on the market. In contrast, others like organization capital and human capital are tightly connected to firms and believed to have low or no liquidation value. A recent debate is whether the average recovery rate of capital goes down when more firms in the economy have a higher fraction of capital as intangible capital.

Second, physical attributes of capital used for production can determine the value of the capital sold in the market. Kermani and Ma (2020*a*) find that the recovery rate is lower when the capital is less mobile, less durable, and more customized. Their estimated industry-average recovery rates for property, plant and equipment (PP&E) range from 10% for certain services industries to 70% for transportation industries. Third, as finance evolves, better creditor rights can ensure a higher recovery rate of capital in place. Mann (2018) finds that court decisions, which increase the pledgeability of patents after 2002, alleviate financial constraints for innovative firms and enable their debt financing and investments. Thus, investigating the impacts of the recovery rate on

both micro-level firms' decisions and macro-level aggregates is important for us to understand the possible results of relaxing financing constraints and rising intangibles in the economy.

At the micro-level, firms' investments are subject to various types of adjustment costs. One of the essential types of cost is financial friction, which has been studied both in corporate finance and macroeconomics. This includes high interest rates related to borrowing-dependent risky debts, bankruptcy costs, and equity issuance costs. Some capital is not collateralizable and has low liquidation value when firms go bankrupt. These characteristics of the capital could lead to higher borrowing costs for firms with a more significant portion of this type of capital and thus to higher financial frictions. Since the firm-level recovery rate of capital is not observable in my CRSP-Compustat merged data sample, I take asset tangibility as a proxy for the recovery rate of capital and calculate the firm-level and industry-level means to study cross-sectional patterns both in the long run and in the short run. I find that: (1) debt-to-sales ratio is positively correlated with asset tangibility; and (2) distance to default is negatively correlated with asset tangibility. These patterns suggest that firms borrow more money and have higher credit risks when the recovery rate is higher. But we are unclear whether these patterns matter for the aggregates and the directions of the effects. We need a model to infer underlying recovery rate parameter and do counterfactuals.

To study the aggregate implications of financial frictions and the varying recovery rate of capital, and to make use of firms' heterogeneity at the micro-level, I take the benchmark firm investment model with risky debt in Strebulaev and Whited (2012) and Gilchrist, Sim and Zakrajšek (2014) which incorporates firms' decisions about capital investment and the recovery rate of capital in my pricing function of risky debts, and combine it with the general equilibrium framework. Firms are homogenous in the first place and heterogeneous afterward due to different realizations of firm-level productivity shocks. Each period, firms decide whether to default on existing debt, how much new debt to issue, how much to invest in capital, and how much new equity to issue. Firms face capital adjustment costs when making nonzero investments. They have to pay nonzero spreads in debt borrowing if there is a likelihood of default. When firms issue new equity, they need to pay equity issuance costs. A representative household completes the model.

This model is hard to solve analytically because of the existence of capital adjustment costs and financial frictions in external financing markets, so I solve it numerically using the dynamic programming and discretization approach in Terry (2017). Parameters describing profitability shocks, capital adjustment costs, and financing costs are the unknowns in the model. In my baseline exercise, I structurally estimate these model parameters in a simulated method of moments (SMM) procedure targeting the variance-covariance matrix of profits, physical investment, and debt

issuance from my main dataset and average values of spread and default rate taken from Bordalo et al. (2021). In particular, the correlation between investments and debt issuance, the average spread, and default rate encode information about the recovery rate of capital, helping to identify the recovery rate.

I draw on a CRSP-Compustat merged data set spanning 2001-2016, which contains information about the financial fundamentals of publicly held companies in the US, and use it to construct my data sample for structural estimation and the micro moments to be matched. For data reasons, my study focuses on publicly held companies, which are relatively large and mature firms. They are the key participants in the debt and equity markets and perform most capital investments in the US. Overall, my estimated model successfully fits the targeted moments. My point estimate of recovery rate is about 74%, and it is about twice the average recovery rate of the property, plant and equipment from US Chapter 11 bankruptcy filings studied in Kermani and Ma (2020*a*).

With this framework and the estimated parameters, I quantify the importance of financial frictions on the aggregate economy by comparing the benchmark economy with economies with different recovery rates and find that aggregate welfare and output are lower, and investment wedge is higher in the economies with lower recovery rates. Aggregate consumption-equivalent welfare decreases by 0.12%, aggregate output decreases by 0.6%, and investment wedge increases by 13% when the recovery rate decreases from 74% to 10%. Aggregate output goes down because of the high micro TFP firms in particular become more constrained, issue fewer debts, and accumulate less capital, although credit risk decreases overall. As the recovery rate goes down, firms borrow less money, and the equilibrium wage decreases. These lead to a lower equilibrium default probability for firms. Once a firm defaults, the value is partially seized by the lenders, and goes to representative household's resource constraints as returns from saving in bonds.

When I directly tackle the issue of intangibles by considering a broader notion of capital empirically, using the definition of total capital in Peters and Taylor (2017), my estimate of the recovery rate of capital is 46%, almost 38% lower than my Baseline estimate. This result implies that intangible capital has a lower liquidation value and a lower recovery rate than physical capital. 46% is also comparable to the average recovery rates of physical capital and identifiable intangible capital studied in Kermani and Ma (2020*a*). By doing a simple counterfactual exercise of decreasing the recovery rate from 74% to 46%, the result suggests rising intangibles could lead to nontrivial loss of output by 0.37% and welfare by 0.11%, although could moderate credit risk. It isn't the hugest possible set of numbers if we allow other model parameters to vary and intangible capital shares continue to rise. The findings in this exercise support that the classic intuitions in the study

that intangibles appear to matter quantitatively.

Literature Review My paper relates to four strands of literature. First, I contribute to the quantitative macroeconomic literature on financial frictions. The classic literature in macroeconomics treats financial frictions, in the form of collateral constraints, as mechanisms that amplify the effects of economic shocks by changing firms' investment behavior (Gertler and Bernanke, 1989; Bernanke, Gertler and Gilchrist, 1999; Kiyotaki and Moore, 1997). Recent studies have tried to measure the aggregate impacts of financial frictions by using quantitative models and data. Financial frictions are typically calibrated by targeting aggregate debt to capital ratio or debt to output ratio of firms (Khan and Thomas, 2013; Midrigan and Xu, 2014; Jermann and Quadrini, 2012). Midrigan and Xu (2014) evaluate the importance of financial constraints for misallocation and development dynamics. Jermann and Quadrini (2012) offer a quantitative exploration of how the dynamics of real and financial variables are affected by "financial shocks". Gilchrist, Sim and Zakrajšek (2014) evaluate the relative importance of financial frictions and uncertainty, and estimate the bankruptcy costs of firms. Catherine et al. (2018) use reduced-form coefficients from empirical corporate finance to make indirect inferences about the parameters in a quantitative model and quantify the output and TFP losses from collateral constraints. I contribute to this literature of financial frictions on macroeconomics by examining the connection between the recovery rate and firms' financial positions in a setting that can be applied to the data. I use a model to match a broad set of financing moments in addition to moments related to production and investment and tries to quantify the aggregate impacts in the long run. In my model, firms can make default decisions, and the average spread and default rate are sizable.

Second, I contribute to a small but growing literature on intangible assets in finance. Eisfeldt and Papanikolaou (2013) investigates the relationship between organization capital and the cross-section of stock returns. Peters and Taylor (2017) show that including intangible capital helps improve the performance of standard q theory. Falato et al. (2020) find that there is an essential connection between intangible capital and the balance sheet and liquidity management decisions of US corporations. Relative to these papers, my main contribution is to estimate the recovery rate of total capital, which is sum of physical and intangible capital, using a quantitative macro model focusing on heterogeneity and a quantified link to micro evidence. The extent of financial constraints is identified by targeting moments constructed with total capital and total investments. Then I use this model and estimated parameters values to explain the potential loss in aggregate welfare and total output because of financial frictions when intangibility in the economy rises.

Third, in the field of structural corporate finance, many people have investigated the determi-

nants of firms' financial positions and what factors matter to match them quantitatively. I follow this literature to construct firms' side problems with investments, external financing, and default decisions. With a similar framework, Hennessy and Whited (2005) develop a dynamic trade-off model to rationalize the behavior of corporate financial data and estimate the pledgeability of physical assets. Hennessy and Whited (2007) allow the firms to default on their debt issued and estimate the deadweight loss that firms experience in bankruptcy. Strebulaev and Whited (2012) provide an excellent overview of the research in dynamic corporate finance and demonstrate the structural estimation process. The structural corporate finance literature makes use of firm-level data and typically targets the average leverage ratio among Compustat firms to estimate parameters about financial frictions. Here, I am estimating the recovery rate of assets by matching both micro moments and macro moments of the CRSP-Compustat merged sample of firms. The extent of financial constraints is identified by targeting (1) the covariance matrix of firms' investment and financing decisions, (2) average spread, and (3) average default rate. While the importance of liquidation value and default risk have been acknowledged in the literature, I develop a quantitative macro model of capital investment and risky debt and use it to establish the quantitative importance of financial frictions to the aggregate economy.

Fourth, several studies in finance consider firms' debt structure and asset pledgeability. Mann (2018) finds that increasing the collateral value of patents enabled debt financing and investment by innovative firms under a natural experiment setting. Chava, Nanda and Xiao (2017) apply regression discontinuity design and find that the increase in value of borrower's patents results in cheaper bank loans. Kermani and Ma (2020*b*) study the data on firms' liquidation values and Chapter 11 going-concern values. They show that firms' physical assets' pledgeability and cash flows can determine their debt capacity. My contribution here is to provide a model-based estimate of the recovery rate instead of using the reduced-form method.

Section 2 describes my data and motivating facts about the relationships between the recovery rate and financial positions. Section 3 develops my heterogeneous firm macro model with capital investments and risky debts. Section 4 introduces my model estimation method and results. Section 5 uses the model to study the implications on aggregate economy with different values of recovery rate. Section 6 provides the estimation results directly targeting moments with total capital. Section 7 concludes. Appendices provide more details on my data, empirical and model analysis.

2 Data and Stylized Facts

In this paper, I investigate the impact of the recovery rate of capital on firms' decisions about financing and investments. When the recovery rate of capital is lower, and the amount of debt issued is fixed, a firm should face higher financial frictions because of higher credit spread and higher default risk. Then they should issue fewer debts than unconstrained firms. But in equilibrium, firms face higher credit risk when the recovery rate is higher because of the increased demand other than the direct effect of increased recovery rate. I will uncover this equilibrium result later with my structural model, which endogenizes credit supply and demand. In this section, I analyze the relationships between proxies for the recovery rate and financial positions and provide suggestive evidence for the model implications. I document that the debt-to-sales ratio is positively correlated with asset tangibility. Distance to default, a predictive measure of default risk, is negatively correlated with the variable.

2.1 Data Description

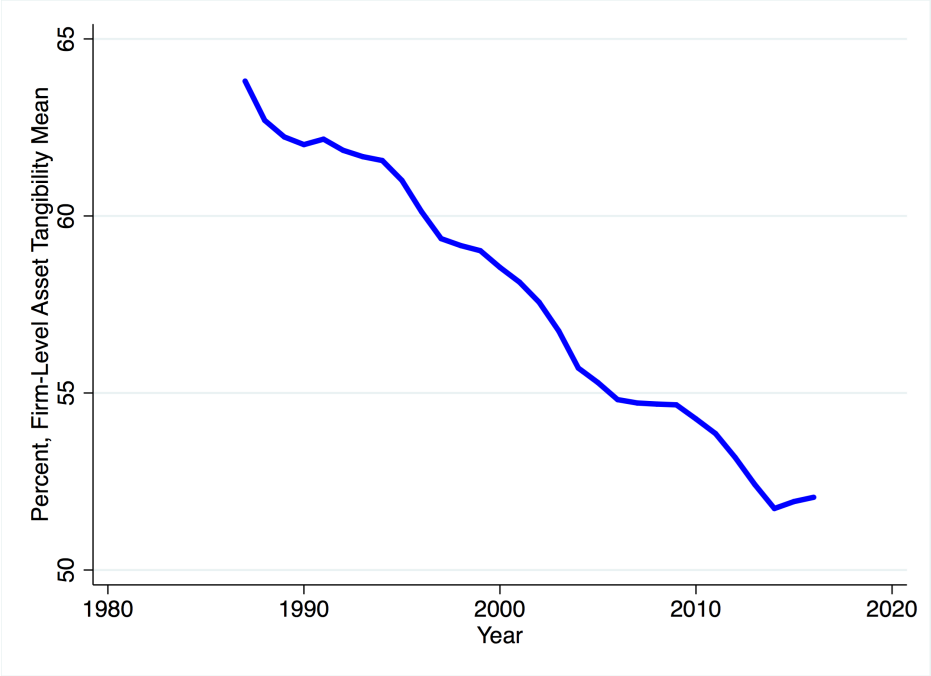
I use data from the CRSP-Compustat merged database to construct a panel of US-listed public firms at an annual frequency from 1987 to 2016 following standard sample-selection criteria in the corporate finance literature.[1] There are two advantages of using this dataset: (1) the panel is long enough for me to use within-firm variations and construct micro-level moments for estimation purposes; and (2) it includes balance-sheet information that allows me to construct variables related to firms' profits, corporate investment and financing decisions.

I start with the measures of firms' capital stock. Firms have both physical and intangible capital. The measure of physical capital is the net book value of property, plant, and equipment recorded on the firm's balance sheet (CRSP/Compustat variable *ppent*). Intangibles are essential inputs for firms' production. In this paper, I assume that intangible investment creates an increase in capital stock instead of leading to increased productivity, adopting the perspective in Peters and Taylor (2017) and Falato et al. (2020). However, intangibles are notoriously challenging to measure since only externally purchased intangible capital appears as intangible assets on the balance sheet. Peters and Taylor (2017) construct estimates of firms' internally created intangible capital by using the perpetual inventory method. They approximate the replacement cost of intangible assets by accumulating past intangible investments. They consider two types of intangible capital: knowledge

[1] Appendix B.1 provides details of data construction.

capital and organizational capital. I take the sum of their estimates of knowledge and organizational capital to measure intangible capital and merge their data into my sample. I then define firm-level asset tangibility as the ratio of physical capital to the sum of physical and intangible capital. Figure 1 reveals that the mean asset tangibility of firms in my sample has declined by around 10% since 1987. This trend is consistent with the finding of rising intangibles in the studies using aggregate data (Corrado and Hulten, 2010, 2014).

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).

To build up capital stock, firms need to make investments. Physical investment is measured as the book value of capital expenditure (CRSP/Compustat variable *capx*). To construct estimates of firms' intangible investments, I follow the approach described in Peters and Taylor (2017). Firms develop knowledge capital while incurring research and development expenses (CRSP/Compustat variable *xrd*) and develop organizational capital while accumulating a fraction of selling, general, & administrative expenses (CRSP/Compustat variable *xsga*). I am counting only 30% of SG&A expenses as an investment in organizational capital, as is general practice in the literature (Hulten and Hao, 2008; Eisfeldt and Papanikolaou, 2014; Peters and Taylor, 2017). I interpret the remaining fraction of SG&A as operating costs. Total intangible investment in each period is measured as the

sum of knowledge capital and organizational capital investments.

In defining financial variables, I construct two measures of firms' financial positions: debt-to-sales ratio and distance-to-default. First, I use the debt-to-sales ratio to measure a firm's external debt financing. I define total debt issued as the sum of long-term debt (CRSP/Compustat variable *dltt*) and short-term debt (CRSP/Compustat variable *dlc*). The debt-to-sales ratio is a unit-free measure and is valid for making comparisons across firms.

Second, I use the Merton Distance to Default model to measure firms' credit risks. Distance to default is the number of standard deviations of the log of a firm's value over debt ratio must deviate from its mean for default to occur. The micro-level aspect of my data allows me to construct this implied probability of default. The variables needed are firms' total debt level, shares outstanding and stock prices. These values are obtained by merging CRSP daily securities data with Compustat quarterly fundamentals data. The literature shows that the measure accounts well for variation in corporate bond prices due to default risk. Gilchrist and Zakrajšek (2012) and Atkeson, Eisfeldt and Weill (2017) have presented evidence showing the tight relationship between distance to default and credit spreads. Distance to default is widely used in the finance industry. Moody's develops its KMV model based on the distance to default and constructs a measure called Expected Default Frequency that implies how likely a company will default on payments by failing to honor the interest and principal payments within one year. Without directly observing firms' bonds market data, distance to default is a proxy to infer a firm's probability of default and credit risks. I follow an iterative procedure based on Gilchrist and Zakrajšek (2012) and Ottonello and Winberry (2020), and use the model equations in Blanco and Navarro (2016) to construct the measure. Using this methodology, I compute the year-ahead distance to default for firms in my sample.

Table 1 contains summary statistics of the final sample used in my reduced-form analysis. Firms are large, with 7,282 million dollars in annual sales and 2,679 million dollars in physical capital stock on average. Moreover, an average firm has 1,926 million dollars in debt outstanding, and the size is comparable to average sales and capital stock. The average intangible investment rate is about the same as the physical investment rate and with similar volatility. The mean asset tangibility is 0.55, so on average 45% of capital is intangible. In terms of financial positions, an average firm has a debt-to-sales ratio of 1.77 and a distance to default of 6.47. The size of the debt is large and volatile. The mean distance to default in my sample is similar to the ones in Gilchrist and Zakrajšek (2012) and Ottonello and Winberry (2020), implying that a six standard deviation shock over a given year will drive the average firm to default. I am going to use the period after 2001 to construct a subsample of my data for structural estimation in Section 4.

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.

2.2 Asset Tangibility

This subsection analyzes the cross-sectional evidence on the relation between firms' asset tangibility and financial positions in the short run and the long run. Firms with higher asset tangibility have a more significant fraction of capital stock as physical capital. The debt-to-sales ratio indicates how large the total debt issued is compared to current sales. A considerable value for distance to default means a significant shock is needed for the firm to default within a year. I document that the debt-to-sales ratio is positively correlated with asset tangibility. Distance to default, a predictive measure of default risk, is negatively correlated with asset tangibility.

Firm-level asset tangibility is defined as the ratio of physical capital to the sum of physical and intangible capital. Some intangible capital like organization and human capital is not identifiable and is believed to have low or no value to be recovered upon defaults. Some intangible capital like patents, technologies, brands, and usage rights is identifiable, and it has liquidation values and can be resold on the market. Kermani and Ma (2020*a*) find that the liquidation recovery rate of identifiable intangible capital is comparable to that of plant, property, and equipment, with an average of 0.35. However, organizational capital, which is not identifiable, consists of around 80% of intangible capital for the average firm as approximated in Peters and Taylor (2017). Thus, firms with lower asset tangibility are more likely to have a lower recovery rate of capital.

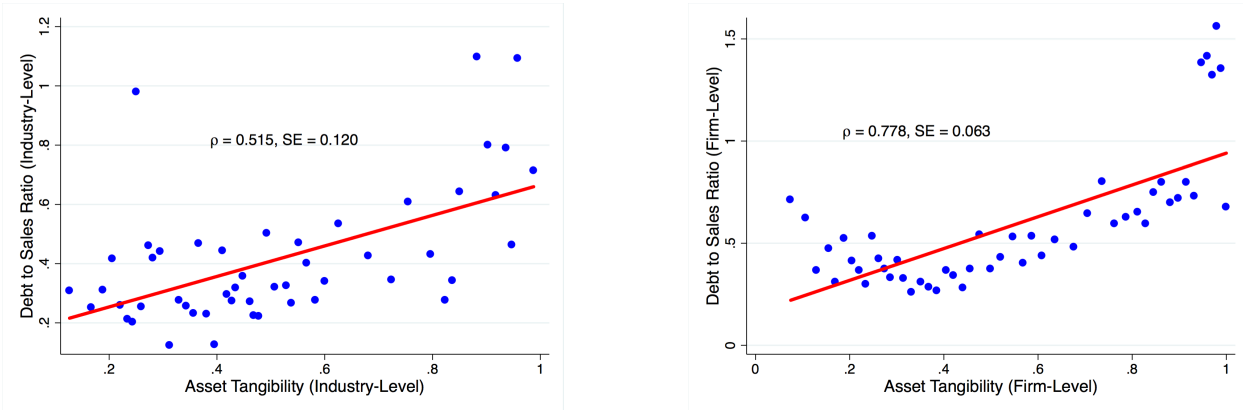
First, I assess the relationship between asset tangibility and firms' debt-to-sales ratio. I separately take averages of industry-level and firm-level observations for all years in my sample

and produce cross-sectional results. Panel A of Figure 2 depicts a binned scatterplot showing the relationship between asset tangibility and debt-to-sales ratio aggregated up to the industry level, showing the best-fit regression line as well. Industry-level averages are calculated by using firm-level observations with the same three digits SIC industry code. The number of sectors is 209. Panel B of Figure 2 presents a binned scatterplot showing the relationship at the firm level, with number of firms as 1142. There is a positive correlation between the debt-to-sales ratio and asset tangibility in the long run. The point estimates of the correlations suggest that a firm with one standard deviation higher in asset tangibility has around 12.5% higher debt-to-sales ratio than an average firm. To investigate the relationship in the short run, I regress the debt-to-sales ratio on asset-tangibility with individual and year fixed effects included. The estimated coefficients in Column (3) and Column (6) of Table 2 suggest that the positive correlation between the debt-to-sales ratio and asset tangibility is statistically significant in the short run. The long-run and short-run results imply that industries and firms with lower average asset tangibility have a lower average debt-to-sales ratio.

Second, I conduct a similar exercise by using distance to default as the variable reflecting firms' financial positions. The binned scatterplots in Figure 3 graph the relationship between asset tangibility and distance to default and reveal that these two variables are negatively correlated. This pattern indicates that firms and industries with lower asset tangibility have a higher distance to default and are more likely to default in the long run. The point estimates of the correlations suggest that a firm with one standard deviation higher in asset tangibility has around 11.03% lower distance to default than an average firm. The cross-sectional results in the short run are reported in Table 3. Although the coefficients of asset tangibility are statistically insignificant when I include individual and year fixed effects at firm-level regression, the point estimates are generally negative, consistent with the relationship in the long run. This imprecise negative relationship may be driven by the fact that firms with a relatively large amount of intangible capital do not borrow much money and always have a low probability of default as a result. Thus, the variations are small, and the coefficient is not precisely estimated.

The stylized facts shown in this subsection indicate a positive link between asset tangibility and debt-to-sales ratio and a negative relationship between asset tangibility and distance to default both in the long run and short run. These patterns are consistent with the idea that financial frictions are more significant for firms with more intangible capital, making them unable to borrow enough to meet funding needs and have lower credit risks in equilibrium. This is an evidence that shows both total borrowing and default rate are higher when the recovery rate is higher. I'm going to build a model that matches this basic fact and also allows for counterfactuals.

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



Panel A. Industry-Level

Panel B. Firm-Level

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 $\rho = 0.778$, $SE = 0.063$, $N^{\text{firm}} = 1142$.

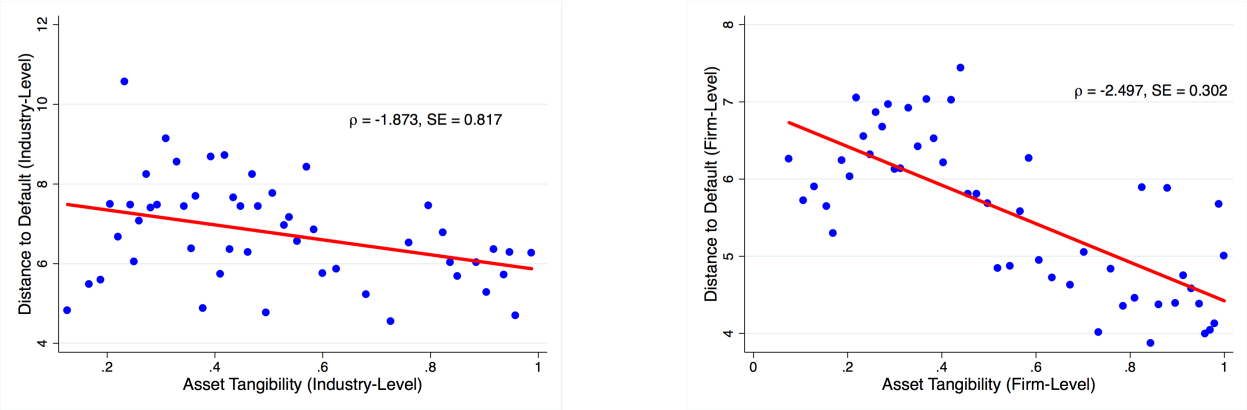
Table 2: Debt-to-Sales Ratio with Asset Tangibility

	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

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

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



Panel A. Industry-Level

Panel B. Firm-Level

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 $\rho = -2.497$, $SE = 0.302$, $N^{\text{firm}} = 1142$.

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

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

3 Model

I now develop a heterogeneous firm general equilibrium model with no macro uncertainty. This is a workhorse neoclassical model with firm heterogeneity and risky debt with the following ingredients: (1) firms use capital and labor as factors of production, (2) they make capital investments subject to capital adjustment costs, (3) they make optimal debt and equity issuance decisions to finance investments with an option to default on debt issued, and (4) part of the capital is recovered upon default. The economy in my model consists of three types of agents: firms, lenders and households. Firms with different and persistent micro-level productivities decide whether to default, invest in capital, issue debt and equity, and hire labor; a continuum of risk-neutral lenders determines the price of risky debts; a representative household completes the model. Time is discrete. I use the prime symbol ($'$) to denote future values. Uppercase letters refer to macro values, and lowercase letters refer to idiosyncratic objects, unless firm-level state variables are shown in parenthesis.

3.1 Firms

Each firm has micro-level TFP z and produces with a decreasing returns-to-scale technology. The firm combines capital k and labor n as inputs to produce a homogenous output good y using a Cobb-Douglas production function

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

The log of micro TFP follows the AR(1) process

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

Firms invest i in capital k subject both to one-period time to build and to depreciations

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

Investment entails quadratic adjustment costs $AC(k, i) = \frac{\phi}{2}(\frac{i}{k})^2 k$.

Firms operate in a competitive market. They are homogenous initially but heterogeneous afterwards due to different realizations of firm-level productivity shocks. Firms differ with regard

to capital stock k and debt level b. Each period, a firm first decides whether to default on its existing debt. If a firm defaults, its assets after depreciation net of deadweight default costs are recovered by lenders, and the firm restarts with zero capital and debt after one period but inherits its previous productivity. If a firm repays its debt issued in last period, it decides how much to invest in capital, hires labor required at wage W, chooses how much one-period debt to borrow and how much new equity to issue. Firms maximize the expected discounted sum of current and future payouts where the discount rate $(1+r)^{-1} < 1$ reflects the real interest rate r pinned down at the equilibrium.

The firm's current dividend is given by

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

where e is the cash flow of the firm:

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

If $e < 0$, the firm needs to issue equity to support its investments, which follows the cost of external equity finance $\eta(e) = \eta_1 |e| \mathbb{1}_{e<0}$, where η_1 is the linear cost parameter. This functional form is a simple way to capture adverse selection costs and underwriting fees for equity issuance costs as in Gomes and Schmid (2010). The firm's profits are given by its output minus wage paid for labor inputs and the adjustment costs for capital accumulation, net of the corporate income tax $\tau \in (0, 1)$. The firm then raises new debt b' with price q yielding total amount equal to qb' and pays back the face value of debt issued in the last period b. Finally, the firm receives tax rebates for capital depreciation and interest expenses on debt.

Given an overall state (z, k, b), I assume that the firm defaults if its net worth realized is lower than zero and it cannot promise to pay back its outstanding liability.[2] The realized net worth is defined as the sum of net profits and undepreciated capital stock, less the face value of debt:

[2] I choose net worth rather than limited liability thresholds to determine default as in Gilchrist, Sim and Zakrajšek (2014). This contract is also like the one in which default is triggered by violating one specific financial covenant. This assumption is equivalent to the assumption that the firm defaults when its equity's value hits the lower bound in a partial equilibrium analysis with an i.i.d. technology shock. It is not clear empirically whether firms declare bankruptcy when the market value of their equity or net asset values become negative. Moreover, this simplifying assumption allows me to avoid the computationally intensive step to calculate default decisions and debt pricing function in each iteration of the dynamic programming routine, which is costly in my general equilibrium framework when doing simulated method of moments procedure for estimation.

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

By combining the expression for net worth with the default condition $x \leq \bar{x} = 0$, we can define a level of micro TFP that triggers default z^D conditional on individual state (k, b):

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

The firm's problem can then be formulated recursively. Upon entering the current period, the value of the firm 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 $V_{ND}(z,k,b)$ is the continuation value when the firm continues operation and $V_D(z)$ is the continuation value when the firm defaults. The continuation value from not defaulting is recursively determined as

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

Since there are no adjustment costs in labor choice, optimal labor demand n is an intratemporal decision depending on current state (z, k, b).

If the firm defaults, its undepreciated capital stock are claimed by lenders net of deadweight costs of default. Then the firm restarts with zero capital stock and zero debt:

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

Equation (5) determines the firm's default policy $df(z,k,b)$ and Equation (6), (7) and (8) determine the optimal policies $k'(z,k,b)$ and $b'(z,k,b)$ if the firm does not default.

3.2 Lenders

Firms receive debt financing from risk-neutral lenders who require an expected return equal to the risk-free rate r. The lenders know the default states corresponding to each possible state (z, k, b). If the firm defaults, lenders recover the firm's undepreciated capital stock less deadweight default costs, so the recovery ratio of debt is

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

which reflects only a fraction γ of capital is recovered when the firm defaults. I assume that the recovered value can only be seized by the lenders at the end of the period.

The endogenous price of risky debt $q(z, k', b')$ is set so that the expected rate of return on debt equals the risk free rate r. This zero-profit condition is

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

The firm's interest rate spread relative to the risk-free rate is

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

3.3 Households

In order to simplify the model, I assume that the economy is populated by a large number of identical households which I can normalize to a measure 1, each of whom solves the same optimization problem. Under these assumptions, I only need to keep track of the decisions of a single representative household. Given wage rate W and real interest rate r, the household solves a standard infinite horizon consumption-labor supply 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 is the dividend from firms and T is tax financed transfers. The household's total income consists of labor income WN, return from savings B, dividend $D = \int d(z,k,b)dF$ and tax transfer T. With these resources the household decides how much to consume C and how much to save B'.

By taking first order derivatives on Equation (10) we can get the optimality conditions as

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

Since there is no aggregate uncertainty in the economy, we can simplify the optimality conditions by imposing stationarity and fixing the aggregate variables

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

3.4 Stationary Competitive Equilibrium

A stationary competitive equilibrium in this economy is a set of prices $\{W, r\}$, debt price schedule q, a set of macro quantities $\{C, Y, I, ACK, ACE\}$, value functions $\{V, V_{ND}, V_D\}$, policy functions $\{k', b', df\}$ and a stationary distribution F such that (1) the household optimizes given W and r; (2) taking W, r, q as given, all firms optimize, value and policy functions solve the dynamic problem of firms; (3) labor market clears $N = \int n(z,k,b)dF(z,k,b)$; (4) bond market clears $B = 0$; (5) 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 distribution $F(z,k,b)$ replicates itself across periods given exogenous shocks and firm decisions.

3.5 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, I solve the model using standard applied dynamic programming techniques detailed in Appendix A.1. The state-space for (z, k, b) is discretized. I transform the AR(1) micro TFP process into a discrete-state Markov chain using the method in Tauchen (1986). The numerical solution proceeds in two steps. First, I 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, I solve a firm's problem using policy function iteration. Then I use the stationary distribution to calculate the aggregate consumption, which clears the goods market. The iteration process continues until the difference between this aggregate consumption and the initial implied aggregate consumption is smaller than the tolerance I set, and the model is solved.

4 Structural Estimation

4.1 Estimation Procedure

I estimate the key parameters of the model via a Simulated Method of Moments procedure because the model has no closed-form solution. I look for the set of parameters $\hat{\theta}$ that minimizes a weighted sum of the difference in model-generated moments $m_S(\theta)$ on simulated data and empirical data moments $m(X)$ from data X:

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

where the weighting matrix W is the inverse of the variance-covariance matrix of data moments, implying an asymptotically efficient SMM estimator. Appendix B.2 provides details of SMM estimation.

4.2 Externally Fixed and Estimated Parameters

My model includes 11 parameters listed in Table 4 and 6. I calibrate 6 of them using estimates from the literature or data counterparts and estimate the 5 remaining ones.

My six externally calibrated parameters are as follows: I set the risk-free rate r to be 4% and the corporate tax rate τ at 20%. Leisure preference parameter ψ is equal to 2.0 based on the

assumption that average households spend 1/3 of time working. The physical capital depreciation rate is fixed at 0.12 as in Falato et al. (2020). For the production side parameters, I set the value of labor revenue elasticity, ν, to be 0.50, and capital revenue elasticity, α, to be 0.25 as in Bloom et al. (2018).

I structurally estimate the remaining 5 parameters by matching a set of both micro and macro moments. These parameters include ρ_z and σ_z that govern persistence and standard deviation of micro-level TFP, ϕ that governs the costs of capital adjustment, η_1 which reflects the linear cost of equity finance. γ, the recovery rate parameter of capital which is the main parameter of interest in this paper.

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. (2020)
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 1/3 of time working

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

4.3 Data Moments

An essential step in the SMM procedure involves selecting the moments to be matched. Hennessy and Whited (2007) suggest: (1) each of the selected moments must be informative about the parameters to be estimated; (2) the moments should include variables that are common in the literature; and (3) the moments should encode information about the firm's real technology. A moment is informative about a parameter if that moment is sensitive to changes in that parameter. A poor choice of moments can lead to large standard errors for the parameters or an unidentified model.

I structurally estimate the unknown parameters through the SMM procedure by targeting moments reported in Table 5. I compute the moments using the CRSP-Compustat merged sample described in Section 2. The micro moments I target are the covariance matrix of profits, investment rate, and debts. I also target two macro moments: average spread and average default rate. These

moments are informative about both financial cost parameters and the technological parameters I seek to estimate.

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

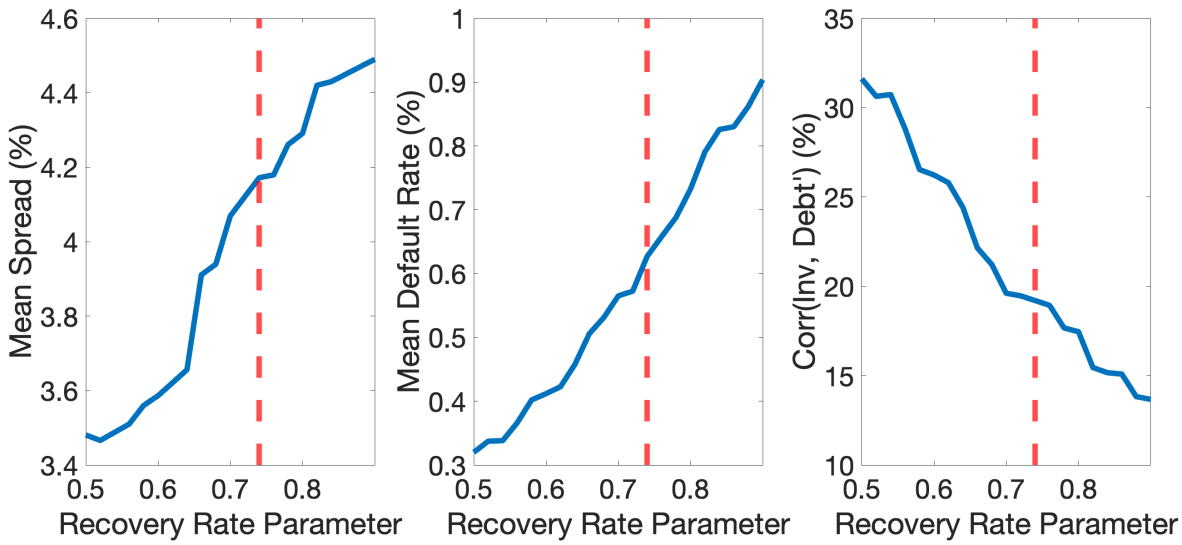
Notes: The micro moments were computed on a sample from CRSP-Compustat merged annual data from 2001-2016, with 7324 firm-years spanning 1022 firms. The reported standard errors for the micro moments are computed using firm-level clustering. An prime symbol (′) indicates future values. Profit, physical 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. (2021).

While all of the moments contain information for all of the estimated parameters, certain moments provide information that is particularly relevant. Firm profits and their correlations are informative about firms' micro TFP process and help to identify ρ_z and σ_z. The volatility of the micro TFP has a direct effect on profit volatility. The variance of investment affects the persistence of micro TFP as well. When shocks are more persistent, firms may choose to postpone their responses. Firms' capital investments volatility and their covariance with profits reflect the capital adjustment costs operating at firms, assisting in identifying ϕ. Adjustment costs compel the firm to smooth its investment policy in response to a productivity shock as indicated by investment variance and indirectly revealed by the correlation with profitability. Debt issuance choices, together with credit spreads, aid in the identification of equity issuance costs. The equity issuance cost parameter governs the amount of debt and equity firms can issue to finance investment.

Finally, the correlation between investments and debt issuance, the average spread and default rate encode information about the recovery rate of capital. I show the local identification of the recovery rate in Figure 4. The mean spread, the mean default rate, and the correlation between investment and debt issuance vary with the recovery rate around my main SMM estimates. The mean spread and the mean default rate are smooth and increasing functions of γ, while the

correlation between investment and debt issuance is a decreasing function of γ. Thus information about these moments helps pin down the recovery rate. Intuitively, firms' debt issuance decisions are constrained for lower values of γ, resulting in low equilibrium borrowing and low credit risk. An increase in the recovery rate allows firms to extract more debt and face a higher equilibrium spread and default rate. When the recovery rate is lower, the correlation between investment and debt issuance is higher, indicating that the firm's debt issuance decision depends more on the investment opportunity. With more enormous financial frictions, firms only issue more debts to finance investment when they need to make significant investments.

Figure 4: 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.

4.4 Estimation Results

Table 6 reports the baseline SMM point estimates and standard errors for my model. The estimated persistence and volatility of productivity are 0.7560 and 0.1606, which are close to the estimates of AR(1) TFP processes from literature in macroeconomics and corporate finance (Hennessy and Whited, 2007; Khan and Thomas, 2013). ϕ, which determines the adjustment cost of capital, is equal to 4.0596. I estimate a cost of equity issuance of 0.0674. It is close to the estimated value of 0.061 for a sample of large firms in Hennessy and Whited (2007), but higher than some other

estimates in the existing literature because they use a functional form that includes a fixed cost parameter of equity issuance besides the linear one. However, it is hard to separately identify the fixed cost and linear cost parameter of equity issuance by using the micro moments I target. The estimated recovery rate of capital is 0.7404, which is close to the higher end of recovery rate estimated in Kermani and Ma (2020*a*), but is smaller than the externally calibrated value in Hennessy and Whited (2007) which is around 0.90. As implied by this model estimate, around 74% of the after-tax undepreciated value of capital could be seized by the lenders if an average firm defaults.

Given the overidentified and nonlinear structure of the model, I am not in general able to deliver an exact match to data moments. Table 7 summarizes the overall model fit by comparing the model-implied moments with their empirical counterparts. The model is broadly successful at quantitatively matching investment and financing policies of US public firms with sizable average spread and default rate, giving me some confidence in the quantitative implications of the model. There are some discrepancies with the data. The volatility of profit in the data is larger. The profits in the data may contain noises caused by transitory shocks or profits manipulation and do not reflect the long-run profits. In my model, I am using the true cash flow, and the volatility is lower. The model also predicts a larger correlation between firm-level debt and profitability than the data indicate. This high correlation is because I only have a single productivity shock in the model, which drives all the variations. A neoclassical model like Real Business Cycle Models usually has this common issue. Introducing additional cost parameters of debt financing or additional shocks may improve the fit. Moreover, I weight the moments optimally using the inverse of my estimate of the moment covariance matrix. The standard error of covariance between profits and debt issuance is large relative to its value, so the weight for this moment will be smaller than others. In the end, the discrepancy for this moment will be relatively larger in the overidentified model. In Section 6, I will show that the model fits much better when parameters are estimated using total capital.

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 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

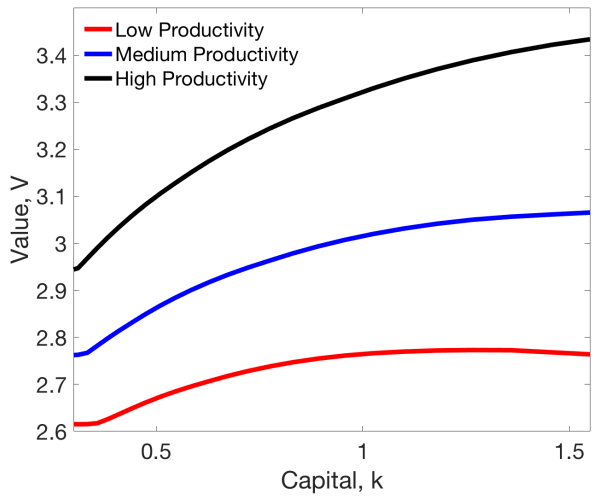
Notes: The data column reports the empirical values of the target moments for my SMM exercise. The model column reports the target moments at my estimated parameters from the Baseline model. The empirical micro moments were computed on a sample from CRSP-Compustat merged annual data from 2001-2016, with 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. (2021). 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.

4.5 Firm Value and Optimal Firm Decisions

Figure 5 plots cross-sections of the value function in my Baseline estimation as a function of capital stock for different micro-level TFP, with debt-to-capital ratio fixed to median value from my stationary distribution. Firm value is high when productivity is high, and it increases as capital k

increases.

Figure 5: 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).

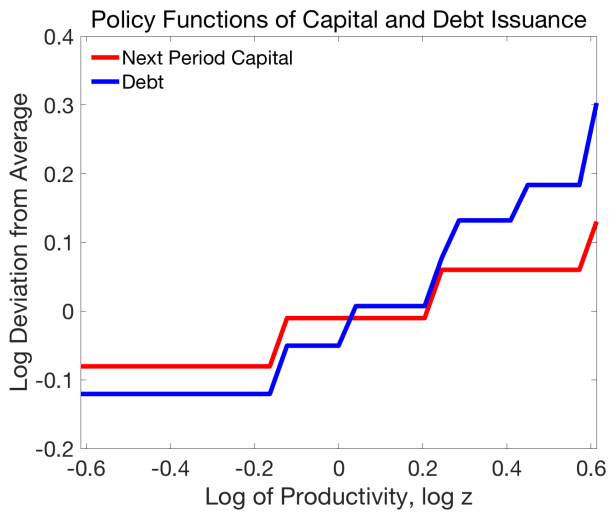
To present the model solution, I plot the model policy functions, which represent optimal capital investment and debt issuance as a function of the log of micro TFP. Both variables are shown as log deviations from the average capital stock and debt values in the ergodic distribution. The policy functions are evaluated with state variables fixed at the average values from my ergodic distribution. Parameters are set to the calibrated and estimated values in Section 4. Figure 6 shows that capital and debt issuance rise with the productivity shock in general.

Figure 7 shows how the price and spread of debt change as the debt-to-capital ratio changes. Panel A illustrates that debt price decreases as the debt-to-capital ratio increases. Panel B plots the spread as a function of the debt-to-capital ratio. With fixed productivity and capital stock, the spread required by lenders is higher when the debt level is higher. Thus, firms face a higher cost of external debt financing with higher debt levels.

5 Changing Recovery Rates

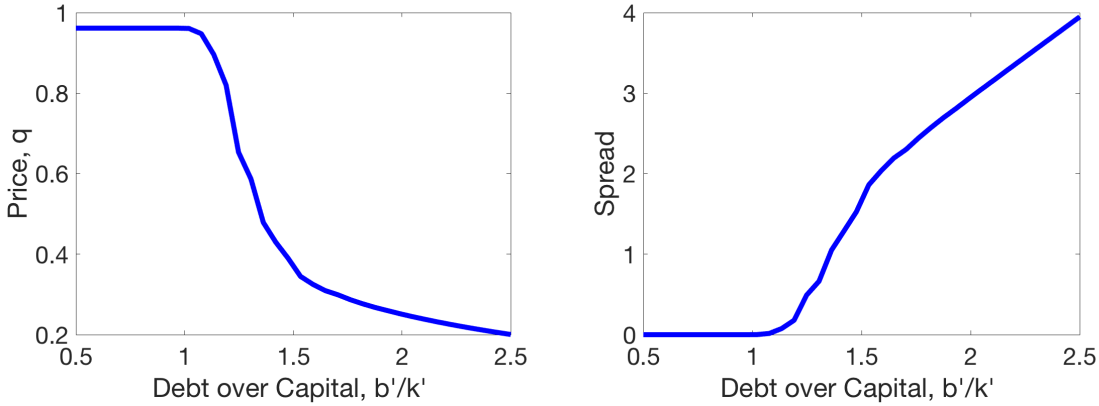
This section evaluates the quantitative aggregate implications of the recovery rate of capital for welfare, total output, aggregate debt issued and investment wedge using a counterfactual exercise.

Figure 6: Policy Function



Notes: The figure plots the policy functions as a function of log of micro TFP z for the estimated model. All lines hold fixed the values of capital k and debt b at the averages 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.

Figure 7: Price of Debt



Panel A. Debt Pricing

Panel B. Spread

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.

I also evaluate the average spread and default rate to study the overall credit risk. In this exercise, I study the model under different degrees of recovery of capital with all other parameters set to the SMM estimated values in my Baseline economy. Comparing the results across these different parameterizations allows me to understand the quantitative importance of the recovery rate.

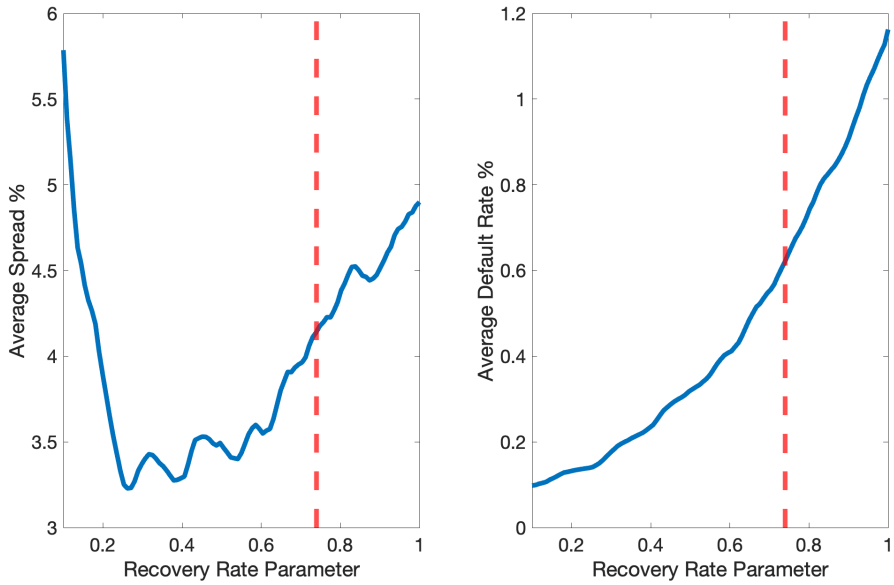
Figure 8 plots the average spread and default rate for the model economy with different recovery rates. The average spread is high when the recovery rate is as low as 0.10. This is intuitive because when the recovery rate is low, lenders could only seize a low value from the capital if firms default and face a high risk. If the firms borrow from the lenders in this case, the spread is high. The average spread increases as the recovery rate increases when the value of γ is around my SMM estimate. The average default rate is low when the recovery rate is low and increases as the recovery rate goes up. These results suggest that firms do not borrow much on average when the recovery rate is low and start to borrow more as the recovery rate goes up. The increase in borrowing drives up the average spread and default rate in the economy.

To better understand why the average spread could go up with the recovery rate, I plot the price and spread of debt as functions of the debt-to-capital ratio with different lines representing different recovery rates in Figure 9. When the recovery rate increases, the price of debt is higher, and the spread is lower with fixed productivity, capital stock, and debt level. Panel B of Figure 9 shows that the spread goes up as debt does for different recovery rates. Spread and default rate can increase for two reasons: credit demand goes up, or credit supply goes down. In this case, the credit supply goes up, so it must be that the credit demand goes up even more and leads to an overall increase in average spread and default rate. Panel B of Figure 9 also indicates that the slope of spread with respect to debt is much flatter when the recovery rate is high compared to the slope with a low recovery rate. Thus, firms find it optimal to borrow more when the recovery rate increases, and the average spread is higher in the equilibrium. The counterfactual exercise later discussed in Section 6 is similar to moving from the black line with a recovery rate of 0.75 to the green line with a recovery rate of 0.45. The slope of spread is steeper when the recovery rate is lower and constrains firms' borrowing.

Figure 10 demonstrates the results of my main quantitative exercise. I use a simple counterfactual experiment in which I keep model parameters fixed at either externally calibrated or structurally estimated values in Section 4 while allowing the recovery rate to vary. The vertical red lines mark the results when the recovery rate is set to my Baseline estimated value.

The results of the quantitative counterfactuals indicate that aggregate output is higher when the recovery rate is higher. Aggregate output changes for more than 1% when the recovery rate increases from 10% to 100%. In macroeconomics, we also care about aggregate welfare. The consumption-equivalent welfare increases as the recovery rate increases. The size of the welfare gain is the percentage increase in each period's consumption to make the Baseline representative household indifferent. Panel A of Figure 10 shows that the net effect on aggregate welfare is

Figure 8: 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.

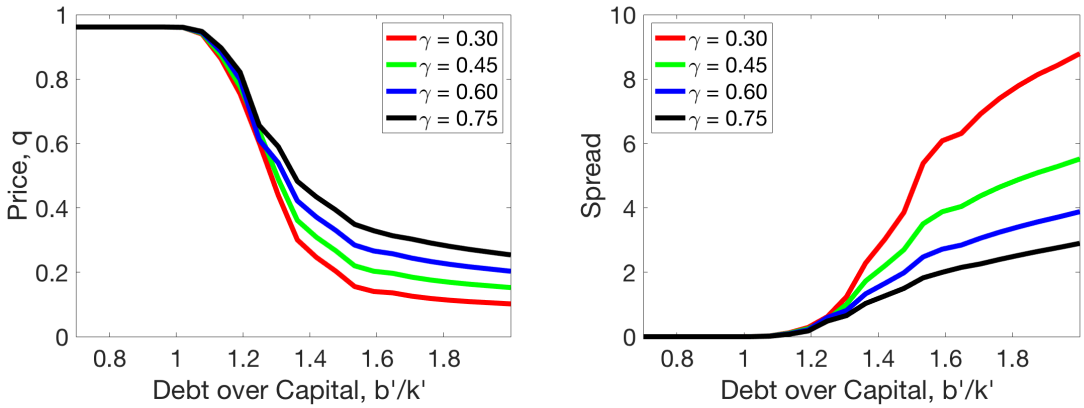
quantitatively sizable. Panel C of Figure 10 demonstrates that the total credit increases by around 8% when the recovery rate increases from 10% to 100%. To study the aggregate impact of financial frictions, I also map my Baseline economy to a prototype economy with efficiency wedge and investment wedge as in Chari, Kehoe and McGrattan (2007).[3] By doing this, we can interpret changes in financial frictions in my Baseline economy as changes in wedges in the prototype economy. Panel D of Figure 10 reveals that the investment wedge decreases considerably when the recovery rate goes up. So when the recovery rate is higher, the investment wedge gets much better, and aggregate welfare can go up.

In Appendix C, I examine the aggregate impacts under a range of alternative values of other estimated parameters other than the recovery rate. Although the magnitude of changes is different, I demonstrate that the implications of the recovery rate are robust in this counterfactual analysis.

I dig deeper into understanding the economic forces that lead to the increases in aggregate welfare and output. Figure 11 shows the changes in the conditional average of output to capital

[3]Appendix A.3 provides details of the prototype economy I use and how to calculate investment wedge and efficiency wedge.

Figure 9: Price of Debt with Different Recovery Rates



Panel A. Debt Pricing

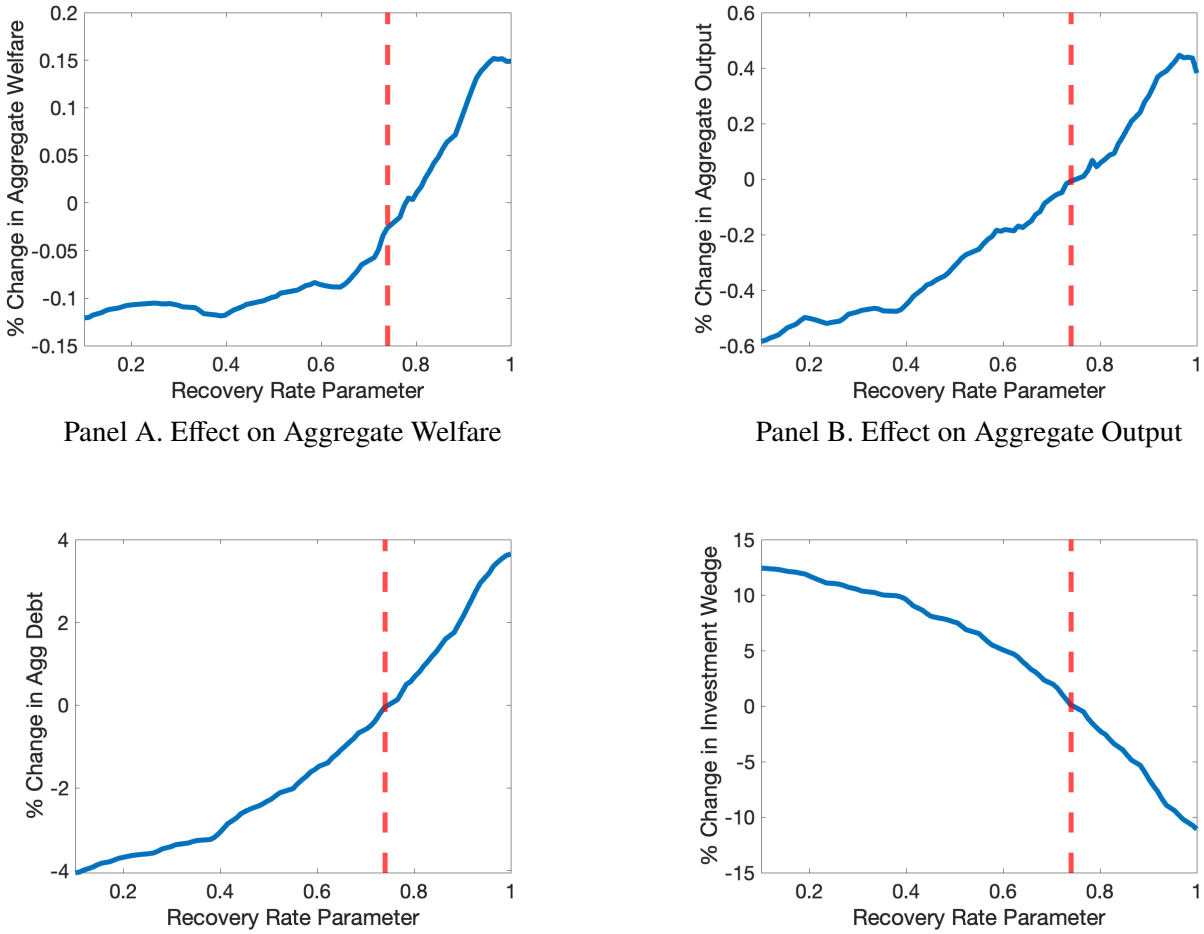
Panel B. Spread

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).

ratio and debt issuance to capital ratio for firms with different productivity levels. The conditional average of firm-level output ratio for high and medium productivity firms decreases as the recovery rate increases while the average for low productivity first increases then decreases. The conditional average of debt ratio increases for all productivity levels, indicating that all firms borrow more when the recovery rate is higher. When the financial constraints are relaxed, the firms find it optimal to borrow more to finance their investments and accumulate more capital. Many of the low productivity firms face high borrowing costs initially and now get the fundings they need and start to produce more output. This explains why the average firm-level output ratio increases when the recovery rate is low. But relatively small fractions of high and medium productivity firms are non-productive initially, and they also issue more debts and accumulate more capital when the recovery rate increases. The effect of increases in debt and equilibrium wage is larger than the effect of the increase in capital, so the average default rates for firms with all different productivity levels are higher in the equilibrium as shown in Figure 12. The value of capital is recovered by the lenders and finally goes to consumer's resource constraint once the firms default. Thus, the increase in output is smaller than the increase in capital on average, and the average output to capital ratio decreases for high and medium productivity firms.

To better present the changes in aggregate variables, I plot the percentage changes for aggregate output and debt contributed by firms with high, medium, and low productivity together with total

Figure 10: Aggregate Impacts of the Recovery Rate



Panel A. Effect on Aggregate Welfare

Panel B. Effect on Aggregate Output

Panel C. Effect on Aggregate Debt

Panel D. Change in Investment Wedge

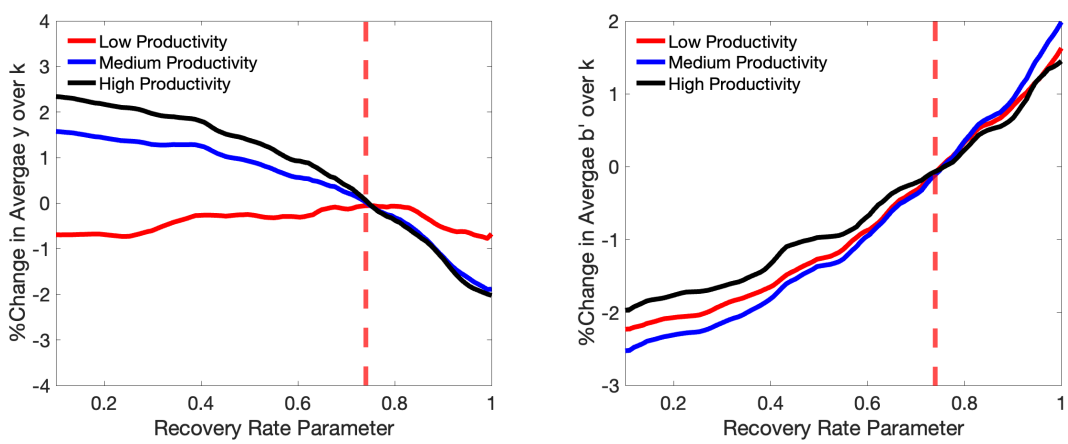
Notes: The figure plots the changes in aggregate consumption-equivalent welfare, aggregate output, aggregate debt issued and capital investment wedge in counterfactual economies with different recovery rates referring to the values in my Baseline economy with the SMM estimated recovery rate. The red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

changes in Figure 13. The aggregate changes are the same as the ones in Figure 10. As the recovery rate increases, the decrease in output produced by low productivity firms almost offsite the increase in output produced by medium productivity firms. The increase of credit risks makes the total output produced by low productivity firms smaller even though those non-defaulting low productivity firms will produce more. The overall increase in aggregate output is mainly driven by the increase in production by high productivity firms. Firms at all different productivity levels issue more debts and accumulate more capital when the recovery rate increases and the financial

constraints are relaxed, as indicated by Panel B of Figure 13. Firms with high productivity are the most responsive ones. These together contribute to the sizable increase in aggregate capital and debt.

The comparisons of changes in the conditional average of output ratio and debt ratio and the contributions to aggregate changes in aggregate variables by firms with different productivity levels show that an increase in the recovery rate relaxes the financing constraints and allows all firms to borrow more money and accumulate more capital. The increases in aggregate output and welfare are mainly contributed by firms with medium and high productivity. Because of the large decrease in the slope of the spread with respect to debt issuance, firms borrow more money when the recovery rate increases, and in equilibrium credit demand goes up more than credit supply does. By market clearing conditions, aggregate consumption and the equilibrium wage also go up together with the recovery rate. The average default rate increases in equilibrium. In summary, the counterfactuals suggest that the recovery rate plays an essential role in affecting aggregate output and welfare through its impact on financial frictions.

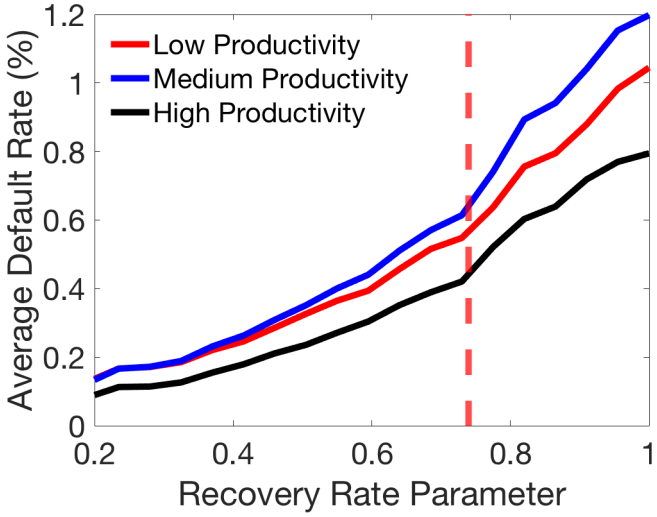
Figure 11: Average y/k and b'/k at Different Productivity



Panel A. Conditional Average of y/k Panel B. Conditional Average of b'/k

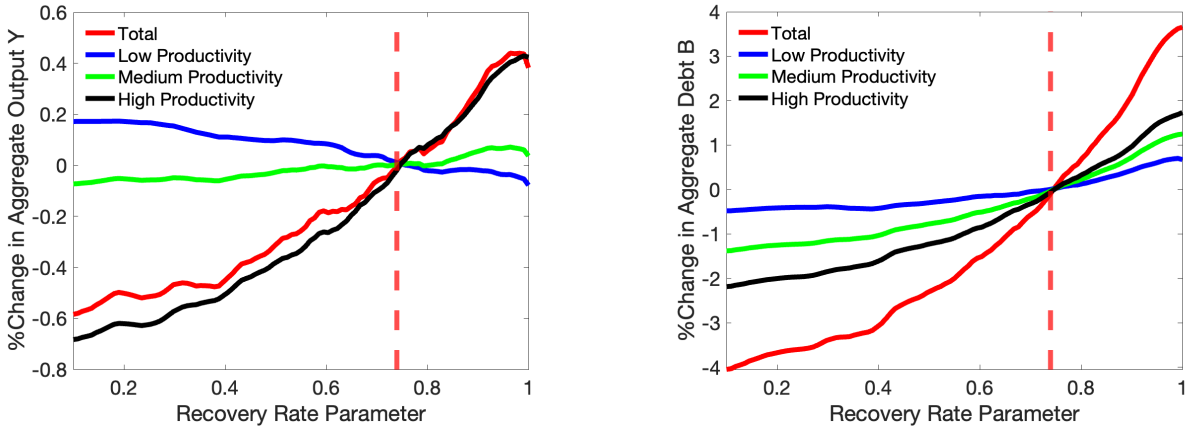
Notes: The figure plots the changes in the average output to capital ratio and debt issuance to capital ratio for firms with different productivity levels. The conditional means are calculated by using the ergodic distribution. The red vertical line corresponds to the SMM estimate of recovery rate γ.

Figure 12: 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.

Figure 13: Changes in Aggregate Variables Contributed by Firms at Different Productivity



Panel A. Aggregate Output

Panel B. Aggregate Debt

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.

6 Intangibles and Recovery

In this section, I investigate the potential aggregate impacts of rising intangibles and declining recovery. I structurally re-estimate the model's key parameters by matching a different set of micro

moments. The micro moments I target are the covariance matrix of profits, total investments, and debts. These three variables are expressed relative to total capital stocks. A firm's total capital stock is the sum of its physical and intangible capital as in Peters and Taylor (2017). Total investments are comprised of physical and intangible investments.

In my Baseline exercise of structural estimation, I only consider physical capital as all the capital stock a firm has, and I construct the variance-covariance matrix only using physical investments. Nevertheless, I also explore the relationship between asset tangibility and firms' financial positions in the empirical exercise of Section 2.2 and take asset tangibility as a proxy for the recovery rate. Here I ask the following questions: what is the model-implied recovery rate of capital when intangible capital is included? Is it less than the Baseline estimated recovery rate, implying that intangible capital has a low liquidation value and consequently a low recovery rate? What are the potential aggregate impacts of rising intangibles through the channel of changing recovery rate?

Similar to the procedure in Section 4, I structurally estimate the unknown parameters through the SMM procedure by targeting moments reported in Table 8. The micro moments I target are the covariance matrix of profits, total investment rate, and debts. I also target two macro moments: average spread and average default rate. Table 9 reports my model's SMM point estimates and standard errors when I target moments related to total capital and total investment. The estimated recovery rate of capital is 0.4676, which is about 37% lower than the Baseline estimated value of 0.7404. This model estimate implies that around 47% of the after-tax undepreciated value of total capital could be seized by the lenders if an average firm defaults. It is consistent with the idea that most intangible capital is not identifiable, and the value is closer to the average recovery rate found empirically in the literature. Thus the recovery rate of total capital is lower than the case when we only consider physical capital. Table 10 summarizes the overall model fit. The model now fits much better with micro moments constructed with total capital. The volatility of profits in the data is much smaller when expenditures in R&D and SG&A are included. The correlation between profit and total investment in my total capital model is closer to the data moment. There is a stronger correlation between total investments and debt issuance. The magnitudes of average spread and default rate also appear to be much better.

To examine the potential quantitative aggregate impacts of rising intangibles, I conduct a simple counterfactual experiment in which I set the recovery rate to the model-implied value I estimate for micro moments calculated with total capital, while fixing all other parameters to their Baseline estimated values. The thought experiment underlying this counterfactual exercise aims to determine how much the aggregate variables will change when firms also use intangible assets for production

and lenders can recover values from intangible capital. Table 11 summarizes the findings. The results of the quantitative counterfactual reveal that increasing the share of intangible capital in firms' assets reduces aggregate welfare by 0.10% and aggregate output by 0.37%. Decreasing the recovery rate from 0.7404 to 0.4676 increases the capital investment wedge by 8.05%, and firms face increased financial frictions. The equilibrium average spread declines by 19.96%, and the equilibrium average default rate declines by 54.22%. In summary, the results of this quantitative counterfactual indicate that the shift toward intangible capital could reduce output and welfare due to the decline in the recovery rate, even though it might also alleviate the credit risk in the economy overall.

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. (2021).

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. (2021). 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.

7 Conclusion

The paper set out to understand how financial frictions interact with firms' capital and financing decisions and quantify the macro impacts of the recovery rate. I use a state of art quantitative general equilibrium heterogeneous firm model with a central role for the recovery rate in determining the allocation of credit and structurally estimate the model parameters by matching micro and macro moments from public firms' data. The SMM estimate of the recovery rate is about 74%. I do a counterfactual analysis of the model by changing the recovery rate with all other parameters set to the SMM estimated values to evaluate the quantitative aggregate implications. The results suggest that declines in the recovery rate reduce aggregate welfare and aggregate output by constraining total credit and capital accumulation. There is a bit of a tradeoff between real quantities and credit risk since the average default rate and spread also decline. These model-implied results validate the signs of my empirics. When I directly tackle the issue of intangibles by considering a broader notion of capital empirically, my estimate of the recovery rate of capital is 46%, almost 37% lower than my Baseline estimate. The counterfactual exercise suggests that rising intangibles could lead to nontrivial loss of output and welfare, although moderating credit risk simultaneously.

Overall, these findings suggest an essential role of the recovery rate and strengthen the idea that relaxing financial constraints is good for aggregate welfare and production. A limitation of this study is that I only consider public firms in my sample. However, these firms are large and mature, and they are the key participants in the debt and equity markets and perform most capital investments. Notwithstanding the relatively limited sample, this work still offers valuable insights into understanding the impacts of the recovery rate and rising intangibility of capital.

Several questions remain to be answered. A natural progression of this work is to separately estimate the recovery rates for different industries and analyze the potential impacts of composition change of the industries in the economy. Further work is needed to understand the implications of rising intangibles fully. We could extend the model in this paper to incorporate firms' decisions about intangible investment and liquidation value of intangible capital in my pricing function of risky debts. It also allows for different revenue elasticity and adjustment costs for intangible capital. The recovery rate of intangible capital could be directly estimated with this structure. Further research could also explore how the changes in debt structure affect firms' decisions and the aggregate economy. Kermani and Ma (2020*b*) find that firms can issue asset-based debt and cash flow-based debt, so the recovery rate of assets is not the only determinant of firms' debt capacity. We could estimate the recovery rate when firms issue cash flow-based debt and investigate the

macro impacts of the recovery rate under this type of debt contract.

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Appendices

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, I solve the model using numerical methods and dynamic programming.

The state space for (z, k, b) is discretized. I 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.

I employ the "inner loop/outer loop" approach to solve this quantitative dynamic general equilibrium model. The numerical solution proceeds in two steps. First, I 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, I solve for a firm's default rule df and compute the implied debt price schedule q according to the lenders' zero-profit condition. Second, I 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, I update the policy functions and repeat the process. After completing the inner loop, I 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 I set, the outer loop is complete, and the model is solved.

A.2 Simulating the Model

After the model is solved, I 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. I 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, I map my Baseline economy to a prototype economy with efficiency wedge and investment wedge as suggested in Chari, Kehoe and McGrattan (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

B.1 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., 2021).

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.

B.2 SMM Estimation

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

B.2.1 Moment and Covariance Matrix Calculation

Table 5 reports a set of 8 target moments at the micro and macro levels for my 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 my CRSP/Compustat merged sample. The sample spans 1022 firms and 7324 total observations. To compute the micro moments, I 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. I use the point estimates and an estimate of the covariance matrix of these two macro moments from Bordalo et al. (2021). 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

$$\sqrt{N}(\hat{m} - m) \to_{d,N\to\infty} N(0, \Omega), \tag{12}$$

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

B.2.2 Point Estimate Calculation

I compute the point estimates estimates $\hat{\theta}$ for the vector of estimated parameters θ in Table 6 and 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. I 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, I solve the model using the “inner loop/outer loop" algorithm in Section 3 and obtain the policy functions as functions of state variables. Then I randomly draw the micro TFP shocks and the simulate an artificial panel containing 5,000 independent and identically distributed firms. I 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. I repeat this procedure until the weighted sum of the differences is minimized.

B.2.3 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

$$\sqrt{N}(\hat{\theta} - \theta) \rightarrow_{d,N\rightarrow\infty} N(0, \Sigma), \tag{13}$$

where

$$\Sigma = (1 + \frac{N}{N^{sim}})(\frac{\partial m_S(\theta)}{\partial \theta'}\Omega^{-1}\frac{\partial m_S(\theta)}{\partial \theta})^{-1}, \tag{14}$$

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, Tables 6 and 9 report standard errors based on the approximating variance from (13).

C Robustness: Aggregate Impacts of the Recovery Rate with Alternative Parameter Values

Here I report the results of a robustness exercise. I examine the aggregate impacts under a range of alternative values of other estimated parameters other than the recovery rate and demonstrate that the implications of the recovery rate are robust in this counterfactual analysis. This section explores how the aggregate impacts of the recovery rate change under a range of alternative values of other estimated parameters. For each experiment, I start from the Baseline estimated model and vary the magnitude of a single parameter in either direction by 5% and plot the aggregate consumption-equivalent welfare, aggregate output, total credit, and capital investment wedge as functions of the recovery rate.

Figure 14 presents the aggregate impacts of the recovery rate when the productivity persistence increases or decreases by 5% relative to the Baseline estimated value. When the persistence is increased by 5%, the changes are similar to those observed under the Baseline. One thing to note is that when the persistence of productivity declines by 5%, the increase in aggregate output are reduced. The change in aggregate welfare is less significant, and the direction becomes ambiguous. In this instance, the investment wedge doesn't decrease significantly when the recovery rate increases, and firms do not respond much to the relaxing financial constraints. Thus, the implication for aggregate welfare depends on the persistence of the productivity process.

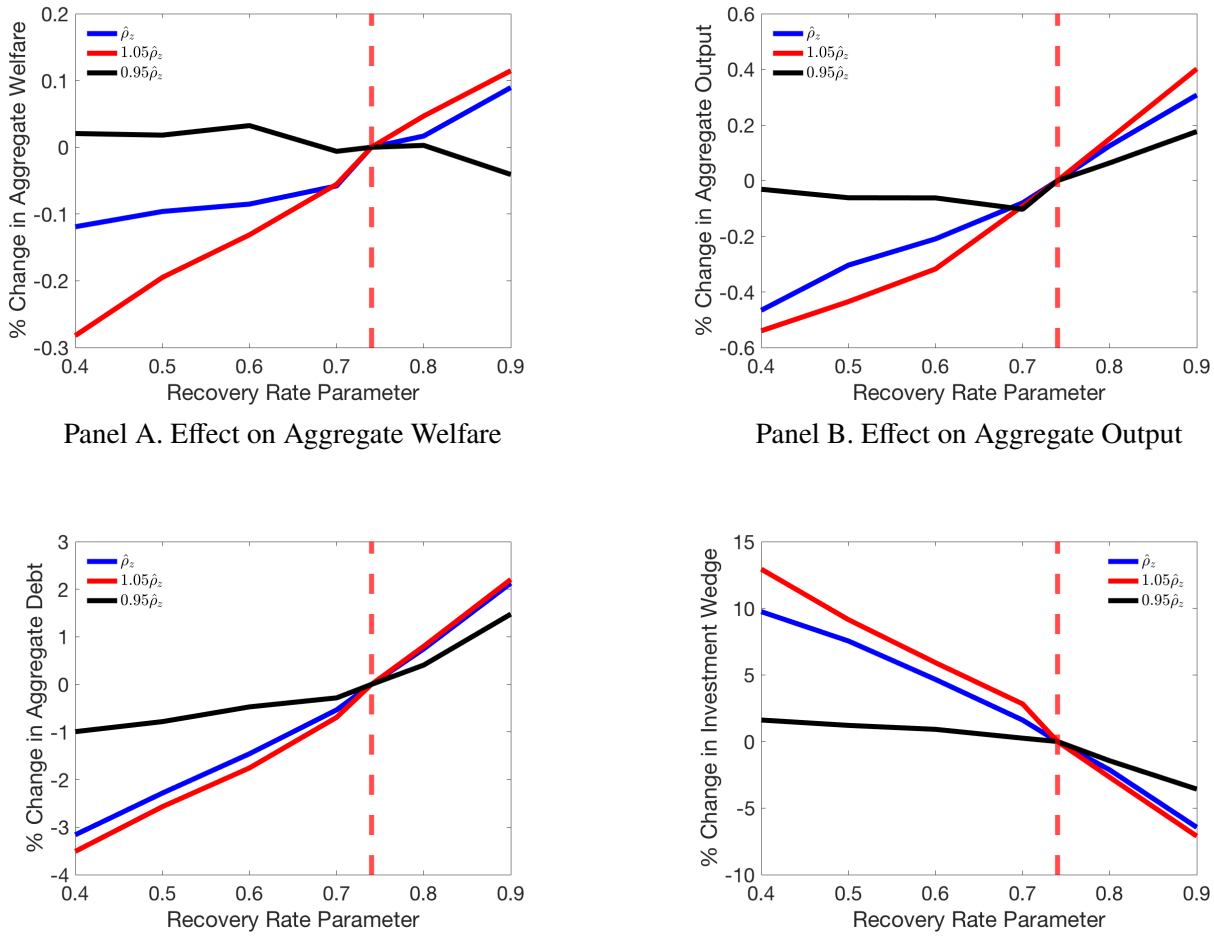
Similarly, when the cost of capital adjustment is increased by 5%, the changes resemble the ones under the Baseline. When the cost of capital adjustment decreases by 5%, the gain in aggregate output become smaller, and the change in aggregate welfare becomes uncertain, as illustrated in Figure 16. This result is because firms can easily adjust their capital stock, requiring less external

financing when the cost of capital adjustment is low. Thus, the impact of relaxing financial constraints through increasing the recovery rate is dampened.

Figure 15 shows the counterfactual results with various values of productivity volatility. When we compare the three lines in each panel of Figure 15, we can notice that the differences in aggregate output and investment wedge are small for the three different values of productivity volatility. Thus the aggregate implication for welfare is similar. I repeat the exercise for the cost of equity issuance as well. Quantitatively, when I vary the size of equity issuance cost in either direction, the changes in the four aggregate variables barely change .

I show in this robustness exercise that the exact magnitudes of the aggregate impacts of the recovery rate alter when other estimated parameter values change. Nonetheless, aggregate output increases qualitatively when the recovery rate increases. The change in aggregate welfare is smaller when productivity persistence and cost of capital adjustment are reduced. Generally, the counterfactual implications of the recovery rate are robust.

Figure 14: Aggregate Impacts of the Recovery Rate for Different ρ_z



Panel A. Effect on Aggregate Welfare

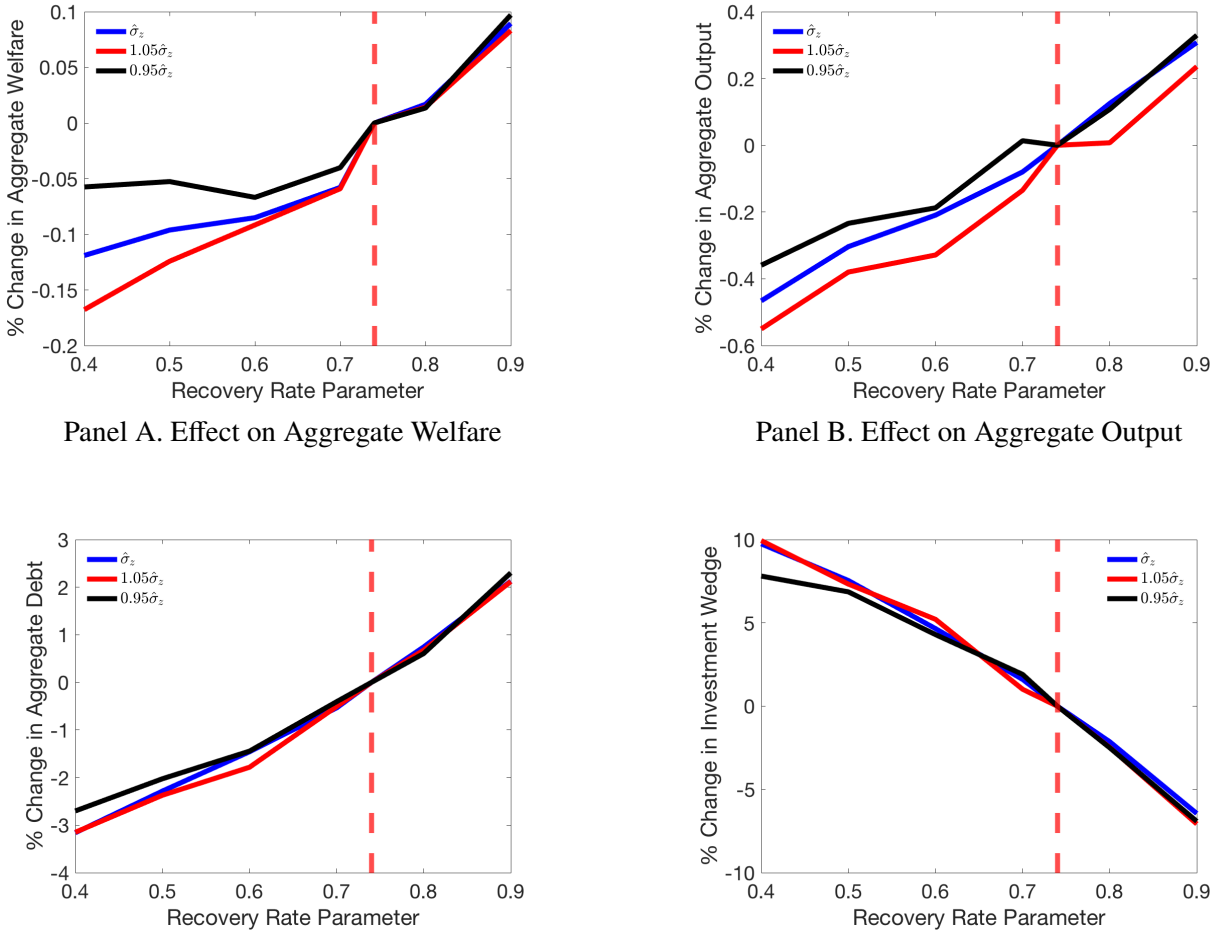
Panel B. Effect on Aggregate Output

Panel C. Effect on Aggregate Debt

Panel D. Change in Investment Wedge

Notes: The figure plots the changes in aggregate consumption-equivalent welfare, aggregate output, total credit 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. The three lines reflect aggregate variables as functions of the recovery rate for different values of ρ_z, with ρ_z equals to Baseline estimated value $\hat{\rho}_z$ (blue line), $1.05\hat{\rho}_z$ (red line) and $0.95\hat{\rho}_z$ (black lines)

Figure 15: Aggregate Impacts of the Recovery Rate for Different σ_z



Panel A. Effect on Aggregate Welfare

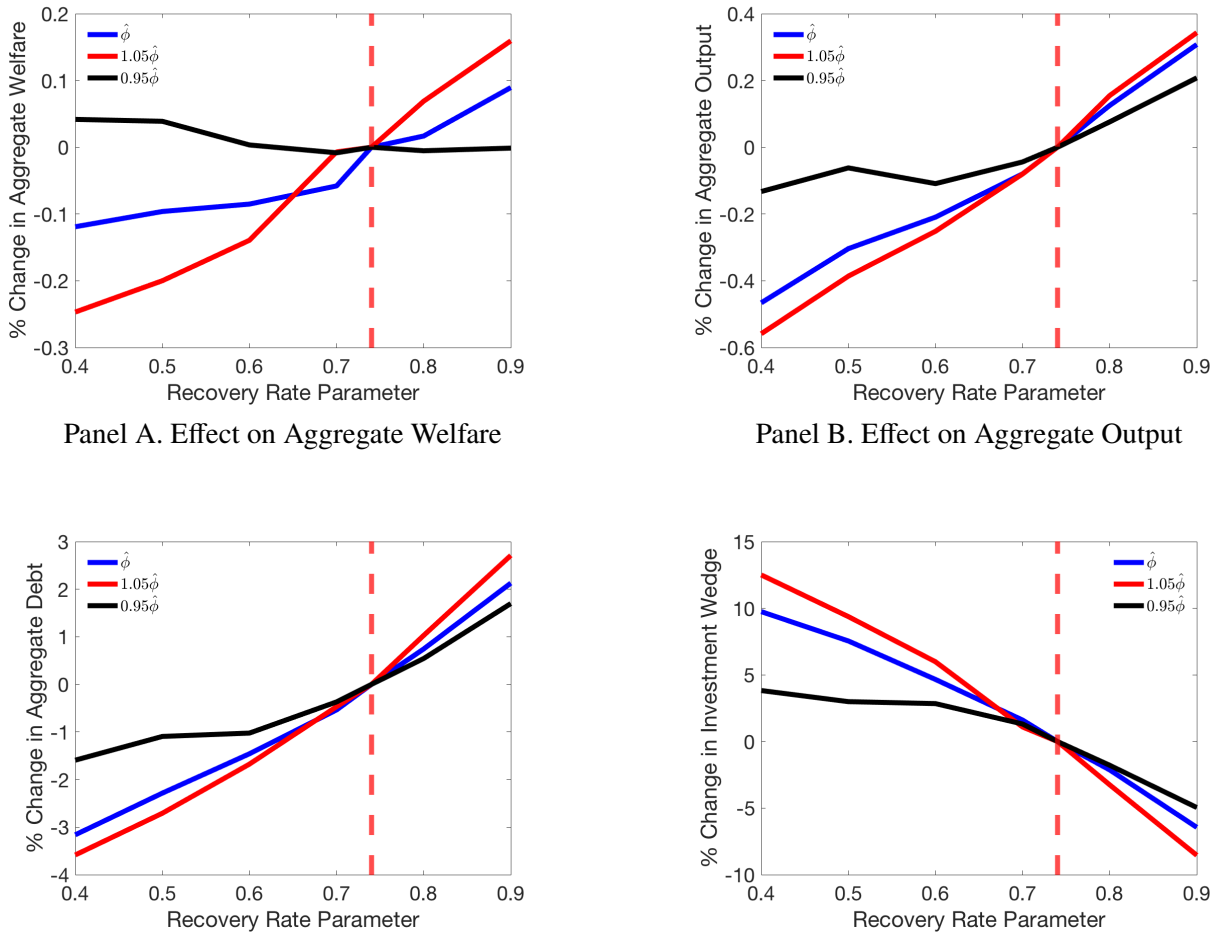
Panel B. Effect on Aggregate Output

Panel C. Effect on Aggregate Debt

Panel D. Change in Investment Wedge

Notes: The figure plots the changes in aggregate consumption-equivalent welfare, aggregate output, total credit 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. The three lines reflect aggregate variables as functions of the recovery rate for different values of σ_z, with σ_z equals to Baseline estimated value $\hat{\sigma}_z$ (blue line), $1.05\hat{\sigma}_z$ (red line) and $0.95\hat{\sigma}_z$ (black lines)

Figure 16: Aggregate Impacts of the Recovery Rate for Different ϕ



Panel A. Effect on Aggregate Welfare

Panel B. Effect on Aggregate Output

Panel C. Effect on Aggregate Debt

Panel D. Change in Investment Wedge

Notes: The figure plots the changes in aggregate consumption-equivalent welfare, aggregate output, total credit 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. The three lines reflect aggregate variables as functions of the recovery rate for different values of ϕ, with ϕ equals to Baseline estimated value $\hat{\phi}$ (blue line), $1.05\hat{\phi}$ (red line) and $0.95\hat{\phi}$ (black lines)