The Cost of Capital and Misallocation in the United States*

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Abstract

We show how to use credit registry microdata to estimate the cost of capital, and how this affects capital allocation efficiency in the United States. Our measure of the cost of capital accounts for the interest rate, expected default probability, recovery rates, and, for floating-rate loans, the expectation of future rates. We find that, on average, the lender's cost of capital closely tracks the five-year Treasury rate, with a spread of 1.5%. Misallocation depends on dispersion in the social cost of capital, which equals the lender's cost of capital plus an agency friction. We find that in normal periods, the implied misallocation is small, resulting in an output loss of only 0.5%. However, the dispersion in the cost of capital rose dramatically during the COVID-19 pandemic, driven by agency frictions. By integrating microdata with a corporate finance framework, this study highlights the resilience of U.S. credit markets under typical conditions, and underscores the inefficiencies that can arise during a crisis.

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1 Introduction

How much does it cost a firm to obtain capital? Economic models often simplify by assuming that all firms can borrow in a competitive market at a common rate. In reality, however, the cost of capital varies significantly across firms. This variation stems not only from differences in stated interest rates but also from firm-specific factors such as default probabilities, loan terms, and lender costs. Such heterogeneity in the cost of capital has profound implications: it can distort the allocation of capital across firms, leading to inefficiencies in economic output. Understanding these inefficiencies is critical for policymakers and researchers seeking to design effective financial and economic policies.

This paper makes two key contributions to the literature. First, we develop a novel methodology that leverages a corporate finance model and uses credit registry microdata to measure the dispersion of the cost of capital. This methodology allows us to quantify how these variations contribute to capital misallocation. Second, we apply this methodology to U.S. credit registry data and uncover two primary insights. While the cost of capital is heterogeneous across firms, the implied misallocation is surprisingly small, suggesting that U.S. capital markets are close to allocative efficiency. However, this efficiency deteriorated in the aftermath of the COVID-19 pandemic, driven primarily by agency frictions.

The methodology we develop offers several advantages. Unlike traditional approaches that require solving structural models computationally, our approach uses sufficient statistics derived directly from moments of the data. This not only simplifies implementation but also provides more robust identification of the sources of misallocation without heavy reliance on calibration assumptions.

Sections 2 and 3 detail the development of the dynamic corporate finance model that forms the foundation of our analysis. This model captures firm-level borrowing, investment, and default decisions in the presence of productivity shocks. We then show how these firm-level dynamics aggregate to influence the allocation of capital across the economy. Importantly, we derive a sufficient statistic for the cost of misallocation which relies on easy to compute moments of the micro data.

Section 4 describes how we map the model to U.S. credit registry data. By defining the cost of capital as the internal rate of return that rationalizes the lender's break-even condition, we compute firm-specific costs of capital. We also develop a formula to measure misallocation based on observed loan characteristics, such as interest rates, default probabilities, and loss given default.

Finally, in Section 5, we present our empirical findings. Using data from more than ninety thousand loans originated between 2014 and 2023, we show that the average cost of capital closely tracks the five-year Treasury rate, with a spread of 1.5%. While the standard deviation of interest rates across loans is 3.6%, the standard deviation of the cost of capital is only 1.6%, reflecting that much of the heterogeneity in interest rates is explained by firm-specific repayment risks. During normal times, the implied output losses from capital misallocation are modest, around 0.5%. However, this loss rose to 1.3% during the pandemic, largely driven by increases in agency frictions.

These findings highlight the resilience of U.S. credit markets in normal periods and underscore the need for targeted interventions during crises to mitigate rising misallocation. By integrating micro-level data with macroeconomic modeling, our approach provides a clearer picture of how financial frictions affect the real economy and offers a foundation for future research into the role of financial policies in addressing misallocation.

Literature Review Our paper contributes to the broader literature on measuring misallocation. Following seminal papers by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), there has been significant work attempting to measure misallocation in different settings (see Hopenhayn (2014) and Restuccia and Rogerson (2017) for literature reviews). An important challenge in this literature is measuring misallocation without imposing strong assumptions on production functions. Haltiwanger et al. (2018) highlight that the standard approach to measuring misallocation is only valid if all firms have the same Cobb-Douglas production function, with the only allowable heterogeneity being a scalar productivity shifter.

Recent work has shown that these issues can be addressed by using (quasi-)experimental variation to estimate marginal products directly (e.g., Carrillo et al. (2023); Hughes and Majerovitz (2023)). However, because experimental variation is rare, these methods have only been applied in limited settings, namely the construction sector in Ecuador and the microenterprise sector in Sri Lanka.

Our paper instead measures heterogeneity in the marginal product of capital from heterogeneity in the cost of capital. This allows us to measure misallocation for a much broader set of firms while remaining robust to arbitrary production functions.

We also contribute to a literature that estimates heterogeneity across firms in interest rates and/or the cost of capital. Banerjee and Duflo (2005) summarize early evidence for substantial heterogeneity in interest rates across borrowers in developing countries, arguing that this heterogeneity implies significant misallocation. Gilchrist et al. (2013) study bond yields in the United States, finding heterogeneity that implies a modest loss of output due to misallocation. Recent work by Gormsen and Huber (2023, 2024) analyzes transcripts of firm earnings calls to extract information on the discount rates and cost of capital that firms use. Cavalcanti et al. (2021) use credit registry data to study heterogeneity in interest rates for borrowing firms in Brazil. They find substantial heterogeneity across firms and use a dynamic structural model with financial frictions to infer the cost of capital. This paper also builds on the findings of Faria-e-Castro et al. (2024), who analyze the dispersion in borrowing rates for U.S. firms using a comprehensive database of loans and bonds. Their study highlights significant heterogeneity in borrowing costs, even within firms, and demonstrates the persistent impact of borrowing costs on firm-level investment and borrowing behaviors.

Relative to this previous literature, our paper makes two key methodological contributions. First, we provide a methodology to estimate a firm's cost of capital from credit registry data. This is not as simple as measuring the interest rate because the cost of capital depends on the ex-ante repayment probability and expected losses given default. Second, we show how to use moments of the distribution of the cost of capital to develop sufficient statistics that allow us to measure the cost of misallocation non-parametrically in a dynamic, stochastic model.

2 Corporate Finance Model

This section outlines the core components of the model, which captures the interactions between borrowers and lenders. We demonstrate how the model's optimality conditions can be derived and integrated with microdata on loan characteristics to estimate the lender's and firm's cost of capital. These rates provide insights into the firm's expected marginal product of capital, a critical metric for assessing misallocation.

Time is discrete and indexed by $t = 0, 1, \ldots$. The economy is populated by firms that borrow and invest, and by lenders who finance those firms.

Borrowers. The borrowers in the model are firms operating in the nonfinancial sector. These firms operate under limited liability and make decisions regarding production, investment, and borrowing. Output is generated using a production function $f(k, z)$, where k represents capital and z denotes productivity shocks.[1] To sustain or expand their operations, firms invest in capital and issue long-term defaultable debt b. In the event of default, lenders recover a fraction $\phi(k)$ of the firm's remaining assets k.

Lenders. Lenders finance firms, with each firm matched to a single lender. Upon matching, the borrower-lender pair draws a realization of ρ, which represents the efficiency of the match.[2] We refer to ρ as the lender's cost of capital. Loans are priced so that lenders break even using ρ as their discount rate, taking into account firm-specific characteristics and risk assessments.

[1] Note that since z can be a vector, this accommodates (stochastic) fixed costs as well as rich heterogeneity in the production function.

[2] This ρ captures both lender- and borrower-specific factors that lie outside the scope of the model, such as the bank's financing costs, risk appetite, or the dynamics of relationship lending. While we do not provide a specific microfoundation for the heterogeneity in ρ, we focus on analyzing its implications.

Firm's Problem. Firms determine their investment and borrowing strategies to maximize their value, taking into account the possibility of future default. The value of repayment for a firm is expressed as:

$$V(k,b,z) = \max_{k',b'} \ \pi(k,b,z,k',b') + \beta\mathbb{E}\left[\max\left\{V(k',b',z'),0\right\}|z\right],$$

where $\pi(k,b,z,k',b')$ denotes the firm's profit function, and β represents the discount factor.

The profit function captures the firm's net return from production and financing decisions:

$$\pi(k,b,z,k',b') = f(k,z) + (1-\delta)k - k' - \theta b + Q(k',b',z)(b' - (1-\theta)b).$$

Here, $f(k,z)$ represents the firm's output as a function of capital k and productivity z, $(1-\delta)k$ accounts for the depreciated value of current capital, and k' denotes new capital investment. The term θb reflects repayment on existing debt, while $Q(k',b',z)$ captures the price of new debt, with $(b' - (1-\theta)b)$ representing the net change in borrowing.

Debt Pricing. Lenders are risk-neutral and price debt based on their cost of capital, ρ. The price of debt $Q(k',b',z)$ is determined as:

$$Q(k',b',z) = \frac{\mathbb{E}\left[\mathcal{P}(k',b',z')\left(\theta + (1-\theta)Q(k'',b'',z')\right) + \left(1-\mathcal{P}(k',b',z')\right)\frac{\phi(k')}{b'}\,\middle|\, k',b',z\right]}{1+\rho},$$

where $\mathcal{P}(k',b',z')$ is the probability of repayment in the next period, and $\phi(k')/b'$ is the recovery rate in the event of default.

The Firm's Cost of Capital. We define the firm's cost of capital, r_t^{firm}, as the ratio of the expected value of future repayments adjusted for the probability of repayment, $\mathbb{E}_t\left[\mathcal{P}_{t+1}(\theta + (1-\theta)Q_{t+1})\right]$, relative to the current price of borrowing, Q_t.[3] Formally, it is expressed as:

$$1 + r_t^{firm} = \frac{\mathbb{E}_t\left[\mathcal{P}_{t+1}(\theta + (1-\theta)Q_{t+1})\right]}{Q_t}. \tag{1}$$

[3]The firm's cost of capital is the implicit interest rate that it pays on its debt.

This equation captures how the firm's borrowing cost depends on repayment probabilities and debt maturity. The firm's cost of capital is one of the key components of the firm's first order condition with respect to capital. Intuitively, we show how to measure r^{firm} in the data, and this will give us information about the marginal revenue product of capital.

Proposition 1 characterizes the firm's cost of capital. All proofs are in Appendix A.

Proposition 1 (Firm's Cost of Capital)**.** *The firm's cost of capital can be written as:*

$$1 + r^{firm} = \frac{1+\rho}{1+\Lambda}, \qquad\qquad \Lambda := \frac{\mathbb{E}_t \left[\left(1 - \mathcal{P}_{t+1}\right) \phi(k')/b' \right]}{\mathbb{E}_t \left[\mathcal{P}_{t+1} \left(\theta + (1-\theta) Q_{t+1} \right) \right]}.$$

The term Λ represents the wedge between the borrower's cost of capital, r^{firm}, and the lender's cost of capital, ρ. This wedge arises due to lender recovery in the event of default. When there is no recovery ($\phi = 0$), the wedge disappears ($\Lambda = 0$), and the firm's cost of capital equals the lender's cost of capital ($r^{firm} = \rho$). On the other hand, when the lender can recover some value after default ($\phi > 0$), the wedge becomes positive ($\Lambda > 0$), and the firm's cost of capital r^{firm} is lower than ρ. This reduction in perceived borrowing cost occurs because the borrower only accounts for states where repayment occurs.

Marginal Revenue Product of Capital. The firm's investment decision follows a standard first-order condition, which equates the firm's cost of capital with its expected marginal revenue product of capital. Formally, this condition is expressed as:[4]

$$(1 + r_t^{firm}) \mathcal{M}_t = \mathbb{E}_t [\mathcal{P}_{t+1} (f_k(k_{t+1}, z_{t+1}) + 1 - \delta)]. \tag{2}$$

The left-hand-side of equation (2) represents the cost of raising more capital. This includes the firm's cost of capital, r_t^{firm}, adjusted by the price feedback multiplier, $\mathcal{M}_t$, which captures the effect of the firm's borrowing and investment on the price of debt. The price feedback multiplier $\mathcal{M}_t$ is given by:

$$\mathcal{M}_t := \frac{1 - \gamma \times \frac{b'}{k'} \times \frac{\partial \log Q}{\partial \log k'}}{1 + \gamma \times \frac{\partial \log Q}{\partial \log b'}}, \qquad \gamma := \frac{b' - (1-\theta) b}{b'},$$

[4] This is a standard result after taking first order conditions and re-arranging terms appropriately.

where γ measures the share of debt tomorrow that will be newly purchased. The numerator of $\mathcal{M}_t$ reflects the feedback from changes in capital on the price of debt, while the denominator incorporates the feedback from changes in borrowing. Together, these terms provide a comprehensive characterization of how price dynamics influence the firm's cost of capital.

The right-hand-side of equation (2) represents the expected marginal revenue product of capital. This term includes the marginal productivity of capital, $f_k(k_{t+1}, z_{t+1})$, and the depreciation factor, $1-\delta$, weighted by the probability of repayment, $\mathcal{P}_{t+1}$.

3 Measuring Misallocation

When financial markets are efficient, all firms face the same cost of capital. However, in the data we find that the cost of capital varies across firms. How does this inefficiency in financial markets translate into an inefficiency in the real economy? We now put our model into general equilibrium in order to study the steady state costs of misallocation arising from dispersion in the cost of capital.

3.1 The Aggregate Economy and Welfare

We begin by setting up the aggregate environment in order to study both the decentralized equilibrium and the planner's problem. The firm's problem will be the same as before. There is an initial unit mass of firms, indexed by i, who exit over time. There is a continuum of firms and no aggregate risk, so aggregates are not stochastic. Firms make undifferentiated products and take the price of their output as given. There is some initial stock of capital K_0, and future capital depends on investment and depreciation through the standard law of motion.

We introduce the notation ω_{it}, which is equal to one if firm i is still operating at time t, and zero if it has exited. Note that $\mathbb{E}_{t-1}[\omega_{it}] = \mathcal{P}_{it}$. Aggregate output is given by:

$$Y_t = \int_0^1 \underbrace{\omega_{it} \cdot f(k_{it}, z_{it})}_{\text{Output if Operates}} - \underbrace{(1-\omega_{it}) \cdot ((1-\delta) k_{it} - \phi(k_{it}))}_{\text{Losses if Defaults}} di \tag{3}$$

Note that we have defined output, Y_t, so that it includes both the firm's output in the event of production, $f(k_{it}, z_{it})$, and the losses from liquidation, $(1-\delta)k_{it} - \phi(k_{it})$, in the event of default. This allows us to define aggregate investment simply:

$$I_t = K_{t+1} - (1-\delta) K_t \tag{4}$$

Finally, aggregate capital is given by:

$$K_t = \int_0^1 k_{it} di \tag{5}$$

The planner wishes to maximize welfare, U, controlling each firm's capital and exit decision. However, the planner is subject to the same information constraints as the firm: k_{it} must be decided in period $t-1$, without yet knowing the productivity or operating costs that will prevail in that period. Exit decisions are made after z_{it} is revealed, but with the values for future periods still unknown.

There is a representative household that obtains utility from consumption: we abstract from inequality to focus on productive efficiency. The household's utility is additively separable over time. Consumption is equal to aggregate output minus investment. Thus, welfare in this economy is given by:

$$U = \sum_{t=0}^{\infty} \beta^t \cdot u(Y_t - I_t)$$

where β is the household's discount rate and u is the utility it gets from consumption.

3.2 The Planner's Problem

Let $S_i^t := \{z_{is}\}_{s=0}^t$ denote the entire history of states, through period t.[5] Define $S^t := \{S_i^t\}_{i\in[0,1]}$ as the collection of all firms' histories. We can use this notation to set up the appropriate constraints to the planner's problem: the planner must set k_{it} as a function of

[5]Note that the only shock in our model is z_{it}, so this is the full history of states.

S^{t-1}, and ω_{it} as a function of S^t.[6] The planner's problem is:

$$
\begin{aligned}
U^* = & \max_{\left\{\{k_{i,t}(S^{t-1}),\omega_{i,t}(S^t)\}_{i\in[0,1]}\right\}_{t=1}^{\infty}} \sum_{t=0}^{\infty} \beta^t \cdot u\left(Y_t - I_t\right) \\
& s.t. \\
& \omega_{i,t}\left(S^t\right) \in \{0,1\}\,\forall i \\
& \omega_{i,t+1}\left(S^{t+1}\right) \geq \omega_{i,t}\left(S^t\right)\,\forall S^t \subset S^{t+1}, \forall i \\
& \text{and Equations 3, 4, and 5 hold}
\end{aligned}
$$

where the inequality $\omega_{i,t+1}\left(S^{t+1}\right) \geq \omega_{i,t}\left(S^t\right)$ notes that if the firm exits, it cannot subsequently re-enter. In period $t = 0$, all firms operate and capital is set exogenously.

We can rewrite the planner's problem as a nested maximization problem, to isolate the intensive-margin choice of capital, holding aggregate capital and the extensive margin fixed. Note that $I_t = K_{t+1} - (1-\delta) K_t$, and so it depends only on aggregate capital (not the allocation across firms). We can thus rewrite the planner's problem in the following nested form:

$$
U^* = \max_{\left\{K_t,\{\omega_{i,t}(S^t)\}_{i\in[0,1]}\right\}_{t=1}^{\infty}} \sum_{t=0}^{\infty} \beta^t \cdot u\left(\left(\max_{\left\{\{k_{i,t}(S^{t-1})\}_{i\in[0,1]}\right\}_{t=1}^{\infty}} Y_t\right) - I_t\right)
$$

with the same constraints as before.

3.3 The Cost of Misallocation

We can now turn our attention to the inner problem. Note that the inner problem is separable across time periods, allowing us to separate it into a sequence of static problems. We focus on the cost of misallocation in terms of output. Simplifying our notation, we can

[6] In practice, since there is no aggregate risk, the planner will only need to use the individual firm's state histories to make decisions.

rewrite the problem as follows:

$$Y_t^*\left(K_t, \{\omega_{it}\}_{i\in[0,1]}\right) = \max_{\{k_{i,t}\}_{i\in[0,1]}} \int_0^1 \mathbb{E}_{t-1}\left[\omega_{it}\cdot f\left(k_{it}; z_{it}\right) - \left(1-\omega_{it}\right)\cdot\left(\left(1-\delta\right)k_{it} - \phi\left(k_{it}\right)\right)\right] di$$

$$s.t.$$

$$K_t = \int_0^1 k_{it} di$$

This problem is now a special case of the environment in Hughes and Majerovitz (2023). We can use their main proposition to derive the cost of misallocation, up to a second-order approximation. Define

$$g_i\left(k_i\right) := \mathbb{E}_{t-1}\left[\omega_{it}\cdot f\left(k_{it}; z_{it}\right) - \left(1-\omega_{it}\right)\cdot\left(\left(1-\delta\right)k_{it} - \phi\left(k_{it}\right)\right)\right].$$

Proposition 2 shows the cost of intensive-margin misallocation.

Proposition 2 ((Special Case of Hughes and Majerovitz (2023)))**.** *The cost of intensive-margin misallocation is given by*

$$\underbrace{\log Y_t^*\left(K_t, \left\{\omega_{it}\left(S^t\right)\right\}_{i\in[0,1]}\right) - \log Y_t}_{\text{Cost of Intensive-Margin Misallocation}}$$
$$\approx \frac{1}{2}\cdot \underbrace{\mathbb{E}_{g_i(k_i)}\left[\mathcal{E}_i\right]}_{\text{Sales-Weighted Elasticity}} \cdot \underbrace{Var_{g_i(k_i)\mathcal{E}_i}\left(\log\left(\frac{\partial}{\partial k_{it}} g_i\left(k_i\right)\right)\right)}_{\text{Weighted Variance of Log Expected MPK}}$$

where $g_i\left(k_i\right)$ is the expected output of the firm as a function of k_i, $\mathcal{E}_i$ is the elasticity of expected output with respect to the cost of capital, $\mathbb{E}_{g_i(k_i)}\left[\cdot\right]$ denotes the weighted average, weighting by $g_i\left(k_i\right)$, $Var_{g_i(k_i)\mathcal{E}_i}\left(\cdot\right)$ denotes the weighted variance, weighting by $g_i\left(k_i\right)\mathcal{E}_i$. All moments are computed for the set of firms that are operating at time $t-1$. The formulas for the expected output of the firm and the elasticity of expected output with respect to the cost of capital are given by:

$$g_i\left(k_i\right) = \mathbb{E}_{t-1}\left[\omega_{it}\cdot f\left(k_{it}; z_{it}\right) - \left(1-\omega_{it}\right)\cdot\left(\left(1-\delta\right)k_{it} - \phi\left(k_{it}\right)\right)\right]$$

$$\mathcal{E}_i = -\frac{\left(\frac{\partial}{\partial k_i} g_i\left(k_i\right)\right)^2}{g_i\left(k_i\right)\cdot\frac{\partial^2}{\left(\partial k_i\right)^2} g_i\left(k_i\right)}$$

Note that in a Cobb-Douglas setting, with $f(k,z) = z \cdot k^{\alpha}$ and no default, the elasticity simplifies to $\mathcal{E} = \frac{\alpha}{1-\alpha}$. In our quantitative analysis, we will calibrate $\mathcal{E} = \frac{1}{2}$, consistent with $\alpha = \frac{1}{3}$. Moreover, note that although the proposition above provides a second-order approximation, it becomes exact in a setting where production is Cobb-Douglas and where productivity and distortions are jointly log-normal (the weights also fall out in that special case).

3.4 The Social Cost of Capital

We have already introduced the notion of the lender's cost of capital, ρ, and the firm's cost of capital, r^{firm}. We now introduce the notion of the social cost of capital, r^{social}. This will reflect the social marginal product of capital at firm i. We define $r^{social}_{i,t}$ as the derivative of aggregate consumption $(Y_t - I_t)$ at time $t+1$ with respect to k_{it+1}, taking expectations at time t (when the investment decision is made).[7] We have:

$$\begin{aligned} r^{social}_{it} &:= \frac{\partial \mathbb{E}_t \left[Y_{t+1} - I_{t+1} \right]}{\partial k_{i,t+1}} \\ &= \mathbb{E}_t \left[\mathcal{P}_{t+1} \left(f_k \left(k_{i,t+1}; z_{i,t+1} \right) + 1 - \delta \right) \right] + \left(1 - \mathcal{P}_{t+1} \right) \cdot \phi' \left(k_{i,t+1} \right) \end{aligned}$$

Combining this with the firm's first-order condition for investment in Equation (2) yields:

$$1 + r^{social}_{it} = \left(1 + r^{firm}_{it} \right) \mathcal{M} + \left(1 - \mathcal{P}_{t+1} \right) \cdot \phi' \left(k_{i,t+1} \right) \tag{6}$$

Note that $1 + r^{social}_{i,t-1} = \frac{\partial}{\partial k_i} g_i(k_i) + 1 - \delta$. This will allow us to use the distribution of r^{social} to measure the cost of misallocation. When we bring this result to the data, we will focus on measuring the variance of r^{social}, and use standard values to calibrate $\mathcal{E}$. Moreover, we will make two further simplifying assumptions. First, we will focus on the unweighted variance, since the weights are difficult to observe in practice. Second, we will use the log-normal approximation $\mathrm{Var}\left(\log \left(r^{social}_{i,t-1} + \delta \right) \right) \approx \log \left(1 + \frac{\mathrm{Var}\left(r^{social}_{i,t-1} + \delta \right)}{\mathbb{E}\left[r^{social}_{i,t-1} + \delta \right]^2} \right)$

To measure misallocation in our data, we combine this with our derivation of r^{social} to yield the following corollary:

[7] Proposition 2 is in terms of gross output, rather than consumption. Nevertheless, we define r^{social} in this way to parallel our definitions of ρ and r^{firm}.

Corollary 1. *Assume that* $\left(r_{i,t-1}^{social}+\delta\right)$ *is log-normally distributed, and also assume that weighted moments can be replaced with unweighted moments. The cost of intensive-margin misallocation is given by*

$$\log Y_t^*\left(K_t,\left\{\omega_{it}\left(S^t\right)\right\}_{i\in[0,1]}\right)-\log Y_t$$
$$\approx\frac{1}{2}\cdot\mathcal{E}\cdot\log\left(1+\frac{Var\left(r_{i,t-1}^{social}\right)}{\mathbb{E}\left[r_{i,t-1}^{social}+\delta\right]^2}\right)$$

This corollary allows us to connect dispersion in r^{social}, an object that we will be able to measure in the microdata, with the cost of intensive-margin misallocation of capital. We next turn to how to measure ρ, r^{firm}, and r^{social} using credit registry data.

4 Empirical Methodology

4.1 Data Sources

We now estimate the three costs of capital: the lender, ρ, the firm, r^{firm}, and the social cost of capital, r^{social}. We rely on the FR Y-14Q dataset (Schedule H.1). This is a quarterly regulatory dataset maintained by the Federal Reserve for stress testing purposes, which contains information on individual loan facilities held in the books of the top 30 to 40 bank holding companies (BHCs) in the US. The Y-14 includes all loan facilities exceeding $1 million and we consider data in the period ranging from 2014Q4 to 2023Q4. Importantly for the purposes of our analysis, the Y-14 contains detailed characteristics of credit facilities such as facility size, origination date and maturity, interest rate or spread, interest rate variability, and the type of loan. Additionally, the Y-14 also covers BHC's risk assessments for each borrower, which include estimates for the 1-year probability of default and loss given default. The probability of default is typically estimated using internal default models that have to be approved by regulators. While there is scope for some discretion in the assignment of these default probabilities (Plosser and Santos, 2018), these models are subject to standardized guidelines following Basel II (BCBS, 2001). We focus on term loans issued to non-governmental and nonfinancial companies based in the US. Our unit observation is a loan origination. Appendix B contains a detailed description of the data cleaning procedure and sample restrictions.

In terms of coverage, Faria-e-Castro et al. (2024) show that the FR Y-14Q Schedule H.1 accounts for 91% of Commercial & Industrial lending undertaken by the 25 largest banks in the US (FRED mnemonic: CIBOARD), and 55% of all Commercial & Industrial lending undertaken by all commercial banks in the US (FRED mnemonic: BUSLOANS). Our focus in term loans and relatively stringent cleaning procedures leave us with a total of 91,873 loans.

4.2 Mapping the Model to the Data

An important difference between the model and the data is the payment structure of loans. In the model, for tractability, we assume that firms borrow in long-term debt that is modeled as a perpetuity with geometrically decaying coupons. In the data, on the other hand, we focus our analysis on term loans with a fixed maturity. This section shows how we map model objects to the data, and how we exploit the Y-14 data to retrieve estimates of the lender's cost of capital, ρ, the firm's cost of capital, r^{firm}, and the social cost of capital, r^{social}.

Consider a generic term loan with principal value B, maturity T, payment schedule $\{D_t\}_{t=1}^{T}$, repayment probability P assumed to be constant over time, and loss given default LGD, also constant over time. The break-even condition for a lender with cost of capital ρ is given by:

$$B = \sum_{t=1}^{T} \left[\frac{P^t D_t + P^{t-1}(1-P)\,(1-LGD)\,B}{(1+\rho)^t} \right],$$

Assume now that the loan is a non-amortizing term loan, with each payment consisting of interest over the life of the loan, and the final payment consisting of a lump-sum principal repayment. Thus $D_t = r_t B$ for $t < T$ and $D_T = (1 + r_T)B$. The interest rate r_t is either a fixed interest rate, or a fixed spread over a floating benchmark rate. We can then rewrite the break-even condition at origination as:

$$1 = \sum_{t=1}^{T} \left[\frac{P^t \mathbb{E}_0 \left[r_t \right] + P^{t-1} (1 - P) \left(1 - LGD \right)}{\left(1 + \rho \right)^t} \right] + \frac{P^T}{\left(1 + \rho \right)^T}, \tag{7}$$

This equation balances the present value of expected payments from the borrower against the lender's opportunity cost, ensuring that the lender breaks even. For a fixed-rate term loan, data on P, LGD, T, r allows us to solve this equation for the match-specific lender's cost of capital ρ.

Floating Rate Loans. The data has loans with either fixed or floating rates. To estimate ρ for floating rate loans, it is necessary to obtain estimates of $\mathbb{E}_0 \left[r_t \right]$, the expected interest rate. Floating rate loans typically charge a reference rate plus a spread. For our analysis, we use smoothed daily yield curve estimates provided by the Federal Reserve Board, based on the methodology described in Gürkaynak et al. (2007). Under the expectations hypothesis, long-term interest rates are assumed to reflect the market's expectations of future short-term rates. Using this framework, we back out $\mathbb{E}_0 \left[r_t \right]$ for each loan by combining the treasury forward rate with the loan's spread. It is important to note that most floating rate loans use LIBOR or SOFR as the reference rate rather than treasury rates. However, for the purpose of this analysis, we treat treasury rates and LIBOR/SOFR as equivalent, as they are very similar during the sample period.

Lender's Cost of Capital. Proposition 3 characterizes the lender's cost of capital, ρ, in the context of fixed interest rate loans.

Proposition 3 (Lender's Cost of Capital)**.** *For a fixed interest rate loan:*

$$1 + \rho = P \left(1 + r \right) + \left(1 - P \right) \left(1 - LGD \right).$$

Where r is the fixed interest rate on the loan. This expression reflects the lender's return, accounting for repayment in non-default states and recovery in default states. A key result for fixed rate loans is that ρ is independent of the loan's maturity T, which simplifies its calculation and interpretation.

For variable rate loans, however, the calculation of ρ requires a numerical solution of the break-even condition presented in equation (7).

Firm's Cost of Capital. Returning to the firm's cost of capital of Proposition 1, we can estimate Λ for term loans, and then solve for r^{firm}. Proposition 4 provides an equation to estimate Λ directly from the data.

Proposition 4 (Firm's Cost of Capital)**.** *We can solve for* Λ *as:*

$$\Lambda = \frac{(1-P)(1-LGD)}{1+\rho-(1-P)(1-LGD)}.$$

The firm's cost of capital is given by:

$$1+r^{firm} = (1+\rho) - \underbrace{(1-P)(1-LGD)}_{Expected\ Recoveries}.$$

In this expression, $(1-P)(1-LGD)$ represents expected recoveries, capturing the key difference between ρ and r^{firm}: lenders benefit from expected recoveries, but borrowers get zero profit in the default state, regardless of whether the lender recovers anything on the loan.

For fixed interest rate loans, the firm's cost of capital simplifies to:

$$1+r^{firm} = (1+r)\,P,$$

where r is the fixed interest rate. This formula reflects how the borrower's cost adjusts based on the likelihood of repayment and default outcomes.

As a result, we are able to measure the firm's cost of capital for each loan in the data at origination. In the next section, we explain how this data can be used to measure the extent of capital misallocation in the economy.

Social Cost of Capital. We can also use the data to estimate the social cost of capital, r^{social}. For measurement, we will specialize and assume that the liquidation technology is linear, meaning it takes the form $\phi(k) = \phi \cdot k$. Combining with Equation (6), this yields a formula for r^{social} in terms of objects in the data.

Proposition 5. *Assume a linear liquidation technology. The social cost of capital is then:*

$$
\begin{aligned}
1 + r^{social} &= \left(1 + r^{firm}\right)\mathcal{M} + (1 - P) \cdot (1 - LGD) \cdot lev \\
&= (1 + \rho)\,\mathcal{M} + (lev - \mathcal{M}) \cdot (1 - P) \cdot (1 - LGD)
\end{aligned}
$$

where $lev := \frac{b_t}{k_t+1}$ *is the firm's leverage ratio.*

In our empirical analysis, we will set the price feedback multiplier $\mathcal{M} = 1$. Under that calibration, the social cost of capital simplifies further:

$$1 + r^{social} = \underbrace{1 + \rho}_{\text{Lender's Cost of Capital}} + \underbrace{(\text{lev} - 1) \cdot (1 - \text{P}) \cdot (1 - LGD)}_{\text{Agency Friction}}$$

The social cost of capital is thus equal to the lender's cost of capital, plus an agency friction. This agency friction reflects the tension between lenders and borrowers. For a firm whose debt is less than its capital (i.e., lev < 1), debt finances only part of the capital, but the entire liquidation value of the capital is used to repay debt. As a result, the lender's return, ρ, is greater than the true social cost of capital, since some of that return reflects a transfer from shareholders to creditors. When lev $= 1$, then there is no transfer and the agency friction is zero.

5 Empirical Results

5.1 Summary Statistics

We provide summary statistics for key variables in Table 1. Our unit of observation is a loan origination, and so all reported firm financials correspond to the financials of the quarter in which that origination took place. The average annual loan interest rate in our sample is 3.87%. These loans have an average expected default probability of 1.38% over the next year, and banks expect to lose, on average, 34.5% of the outstanding value of the loan in the event of default. As a result, the lender's cost of capital, ρ, averages 3.56%. [8] The social cost of capital and firm's cost of capital are even lower, at 3.29% and 2.64% respectively.

Interest rates vary across loans, with a standard deviation of 1.5%, reflecting heterogeneity both within and across time. The lender's cost of capital shows slightly less heterogeneity, with a standard deviation of 1.48%. In contrast, the social cost of capital and firm's cost of capital have higher heterogeneity, with standard deviations of 1.84% and 2.48%. It is not surprising that the firm and social cost of capital vary more than the lender's cost of capital, because they include wedges that add to the variance. Even if the financial market were efficient from the lender's perspective (i.e. if the lender's return were equalized across all loans), these wedges would still create variation in r^{firm} and r^{social}.

Why does the lender's cost of capital vary less than the interest rate? To build intuition, we can focus on the formula for the lender's cost of capital, ρ, for fixed rate loans. With some rearrangement, the lender's cost of capital can be expressed as $\rho = r - (1 - P)(r + LGD)$. Since r is small at annual frequencies compared to LGD, we can use the approximation $\rho \approx r - (1 - P) \cdot LGD$. This yields the variance decomposition

$$\text{Var}(\rho) \approx \text{Var}(r) + \text{Var}((1 - P) \cdot LGD) - 2 \cdot \text{Var}(r, (1 - P) \cdot LGD)$$

The variance of ρ is smaller than the variance of r because of the covariance term: interest rates are higher when the lender's expected losses, $(1 - P) \cdot LGD$, are high.

We view these results as a vindication for our method of estimating the cost of capital. If our measures of default probabilities and recovery rates were just noise, then the variance of the lender's cost of capital would be substantially greater than the variance of interest rates: the covariance term would be zero, and the term $\text{Var}((1 - P) \cdot LGD)$ would push the variance of ρ substantially above the variance of r. Instead, the variance of the cost of capital is smaller, suggesting that default probabilities and recovery rates covary with interest rates in the way that we would expect in a financial market that is close to efficient.

[8] The negative covariance of r and P means that the average ρ is lower than we might have expected from the raw averages of P, r, and LGD. For fixed rate loans, $1 + \rho = P(1 + r) + (1 - P)(1 - LGD)$; the average value of $P(1 + r)$ will be brought down by the fact that P is low when $(1 + r)$ is high.

Table 1: Summary Statistics

	Mean	SD	p10	p50	p90
Interest Rate	3.87	1.50	2.10	3.75	5.81
Maturity (years)	6.47	4.41	3.00	5.00	10.00
ρ (%)	3.56	1.48	2.02	3.53	5.28
r^{firm} (%)	2.64	2.48	0.93	2.84	4.68
r^{social} (%)	3.29	1.84	1.67	3.30	5.12
Prob. Default (%)	1.38	2.18	0.19	0.91	2.65
Loss Given Default (%)	34.53	13.17	18.00	35.45	50.00
Loan Amount (M)	11.33	68.38	1.12	2.68	24.90
Sales (M)	1,418.73	6,124.29	2.39	67.41	2,239.46
Assets (M)	2,026.70	9,260.13	1.51	41.54	2,703.83
Leverage (%)	64.93	34.23	28.83	63.17	95.29
Return on Assets (%)	22.64	29.10	4.70	15.55	44.20
N Loans	61910				
N Firms	35063				
N Fixed Rate	28183				
N Variable Rate	33727				

5.2 Averages by Quarter of Origination

We begin by analyzing the time series of average values, by quarter of origination. The key inputs into our measures of the cost of capital are the interest rate, default probability, and loss given default. We first analyze the behavior of these averages over time, in Figure 1. We separate the interest rate time series into interest rates on fixed-rate loans and the spread for variable-rate loans. During the time period we study, interest rates fall and then rise concurrent with the movement of monetary policy; average spreads are very stable, ranging from 1.9% to 2.3%. Default probabilities show a modest upward secular trend, along with a temporary spike around the time of the COVID-19 pandemic. Expected losses given default fall around the onset of the pandemic, implying that banks expect larger recoveries in the event of default. Note, however, that the magnitude of the change in recoveries is sufficiently small that it has little effect on ρ, since this change is multiplied by the (small) probability of default.

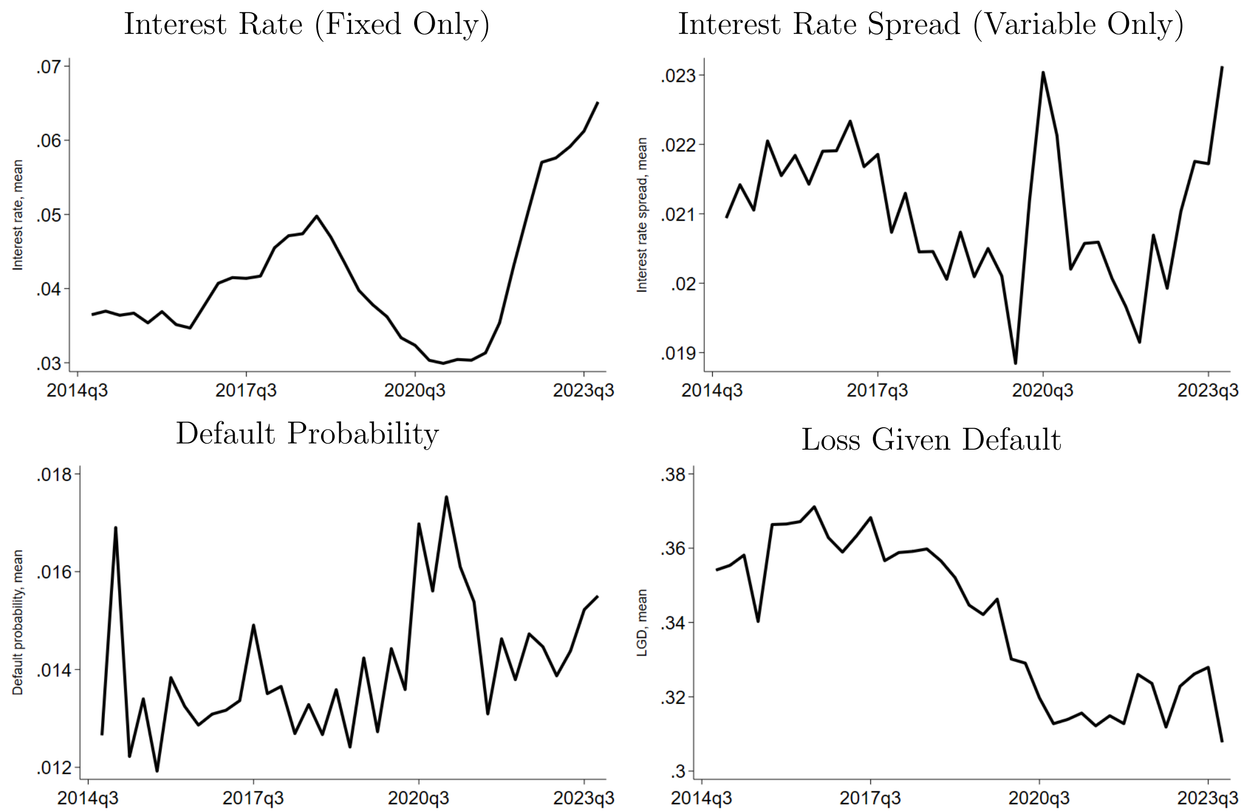

Figure 1: Averages by Quarter of Origination (r, Spreads, Default Probability, and LGD)

Next, in Figure 2, we plot the lender's cost of capital, ρ, the firm's cost of capital, r^{firm}, and the social cost of capital, r^{social}, against the five-year treasury rate. In computing r^{social}, we set $\mathcal{M} = 1$. The lender's cost of capital is nearly identical to the average r^{social}, and both rates covary strongly with the five-year treasury rate. There is an average spread of roughly 150 basis points between the lender's cost of capital and the treasury rate, although it has a delayed reaction to movements in treasury rates: the spread is initially stable at 150 basis points, then rises above the average when treasury rates fall and falls below the average once treasury rates rise again. Note that the lender's cost of capital is already adjusted for default risk, and so this cannot explain the spread relative to treasuries. The social cost of capital, r^{social} is quite close to ρ. In contrast, the firm's cost of capital, r^{firm}, tracks the treasury rate more closely with a small spread.

While our analysis takes into account the maturity of the loan, there are potential con-

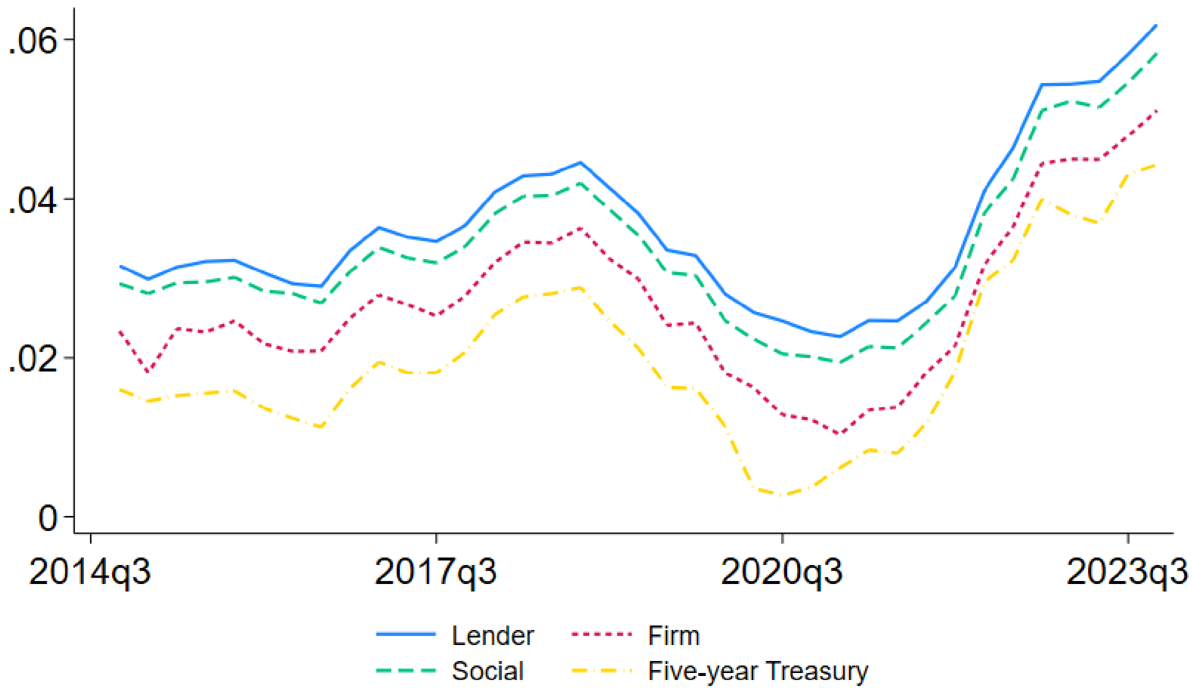

Figure 2: Averages by Quarter of Origination (ρ, r_{firm}, r_{social}, and Five-Year Treasury Rate)

cerns that loans of different maturities may face different rates, even if they reflect a constant spread on a the (time-varying) risk-free rate. To mitigate these concerns, in Appendix C, we recompute our analysis focusing on fixed-rate, five-year loans. This is the most common maturity for fixed rate loans. Focusing on fixed-rate loans is convenient because it is not sensitive to the term structure of the loan, nor to estimates of expected future rates derived from the yield curve. Five-year loans are also convenient because they allow direct comparison to the five-year treasury rate. The average cost of capital for fixed-rate, five-year loans is very similar to the overall sample: there is a roughly 150 basis point spread relative to five-year treasuries, following the same dynamics as in the overall sample.

5.3 Cross-Sectional Heterogeneity

We next turn to study the cross-sectional heterogeneity in interest rates and to the cost of capital.

To begin, we decompose the variance into time, firm, and bank fixed effects. We follow the variance decomposition of Daruich and Kozlowski (2023). To ensure that we can estimate firm level fixed effects we subset our sample to the set of firms with five or more distinct loans. We then progressively add time, firm-time, and bank-firm-time fixed effects, building to the fixed-effects specification in Equation 8 below, where i indexes firms, τ represents the quarter of origination, b indexes banks, and l represents the particular loan.

$$r_{i\tau bs} = \alpha_i + \gamma_{i\tau} + \delta_{i\tau b} + \varepsilon_{i\tau bs} \tag{8}$$

The results are in Table 2. The time fixed effect explains 61% of the variance in interest rates and 50% of the variance in the lender's cost of capital. Adding in firm time fixed effects explains an additional 24% of the variance of interest rates, and 25% of the variance in the lender's cost of capital. Results are similar for the social cost of capital, while the firm's cost of capital behaves somewhat differently: only 23% of the variance is explained by time fixed effects, but adding in firm-time fixed effects explains another 35% of the variance. For all four variables, the adding in bank-firm-time fixed effects explains a negligible share of the variance (at most 1.12%, for r^{firm}), suggesting that heterogeneity across banks is not an important explanation of heterogeneity in interest rates or the cost of capital.

	Time	Firm	Bank	Residual
Interest rate	60.76	24.00	0.29	14.94
ρ	50.18	25.42	0.68	23.72
r^{firm}	23.11	35.02	1.12	40.75
r^{social}	40.38	29.78	0.85	28.99
N Firms	1907			
N Securities	18434			

Table 2: Variance decomposition of interest rates and cost of capital (ρ, r^{firm}, and r^{social})

We also explore the correlation between the cost of capital and firm-level covariates. We regress $\log(1+r)$ separately on log leverage, log return on assets, and log assets. We conduct this analysis for interest rates, ρ, r^{firm}, and r^{social}. The results are shown in Tables 3, 4, 6, and 5. Of the three covariates, the best predictor is the return on assets; interest rates and the cost of capital are consistently higher at firms with high return on assets. Although we cannot attach a causal interpretation to the estimated coefficients, this would be consistent with a model where causality runs from the cost of capital to firm decisions: firms with a higher cost of capital will demand a high return on their investments. Yet perhaps more notable is the very low R^2. The return on assets explains between 2 and 3% of the variance, depending on the measure of the cost of capital, with other covariates explaining less than 1%. Firm-level covariates explain approximately none of the variance in the cost of capital.

	(1)	(2)	(3)
log leverage	0.006		
	(0.00)		
log roa		0.132***	
		(0.02)	
log assets			-0.096***
			(0.00)
Observations	61583	1659	61902
Adjusted R^2	0.000	0.017	0.009

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Regression of $\log(1 + r)$ on covariates

	(1)	(2)	(3)
log leverage	-0.012***		
	(0.00)		
log roa		0.144***	
		(0.03)	
log assets			-0.016***
			(0.00)
Observations	61583	1659	61902
Adjusted R^2	0.000	0.020	0.000

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression of $\log(1 + \rho)$ on covariates

	(1)	(2)	(3)
log leverage	-0.045***		
	(0.00)		
log roa		0.172***	
		(0.03)	
log assets			0.070***
			(0.00)
Observations	61583	1659	61902
Adjusted R^2	0.002	0.029	0.005

Standardized beta coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regression of $\log(1 + r^{firm})$ on covariates

	(1)	(2)	(3)
log leverage	0.139***		
	(0.01)		
log roa		0.134***	
		(0.03)	
log assets			0.008*
			(0.00)
Observations	61583	1659	61902
Adjusted R^2	0.019	0.017	0.000

Standardized beta coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regression of $\log(1 + r^{social})$ on covariates

5.4 Misallocation

What does the heterogeneity in the cost of capital imply for the cost of misallocation? To answer this we use our approximate formula for misallocation from Corollary 1, calibrating $\mathcal{E} = 1/2$, $\mathcal{M} = 1$, and $\delta = 0.06$.[9] Our calibrated value for $\mathcal{E}$ is standard, and consistent with a production function of $f(k, z) = zk^{1/3}$. We compute the MPK as $r^{social} + \delta$, and then compute Var($\log MPK$) using the log-normal approximation $\text{Var}(\log MPK) \approx \log(1 + \text{Var}(MPK)/E[MPK]^2)$. [10] We compute this statistic by quarter of origination, in order to focus on within-period misallocation. Our model does not contain aggregate shocks, and we would thus need a richer model to study misallocation across time. We interpret our results below as reflecting what misallocation would be for an economy that remained in the same steady state.

We find that the misallocation of capital resulting from heterogeneity in the cost of capital, plus the agency friction, is small. We plot our estimates in Figure 3. In the period before the COVID pandemic the implied misallocation is flat and low: formally reallocating capital across firms would increase aggregate output by 0.5%. This number rises dramatically with the onset of the pandemic, averaging 1.3% during 2020 and 2021, before falling back to a somewhat elevated 0.7% in 2022 and 2023.

Our model of misallocation studies an economy in steady-state, which complicates the interpretation of short-run changes in the distribution of the cost of capital. A temporary shock to the dispersion of r^{social} among newly originated loans will have only limited effects on the dispersion of r^{social} in the full population of firms. Moreover, a steady-state model with no aggregate shocks is not well suited to studying aggregate dynamics in response to a shock. Thus, we caution against over-interpreting the transitory rise in implied misallocation

[9] Note that in steady state $\delta = \frac{I/Y}{K/Y}$. In the data, at the annual frequency, the capital-output ratio is about 3 while the investment-output ratio is about 0.18 (we measure capital as BEA Current-Cost Net Stock of Fixed Assets and investment is GDPI in FRED). Hence, at an annual frequency, $\delta = 0.06$.

[10] We follow Hughes and Majerovitz (2024) in using the log-normal approximation rather than computing the variance of $\log MPK$ directly. Using $\log MPK$ directly will in general be very sensitive to outliers with low MPK.

during the pandemic: if the increased dispersion of r^{social} were permanent, then misallocation would rise by 0.8% in steady state, but it is not obvious how much misallocation actually rose in response to the transitory shock. Instead, our main takeaway from the analysis is that in "normal times" (e.g. before the pandemic), heterogeneity in r^{social} implies a very small cost of misallocation in steady state.

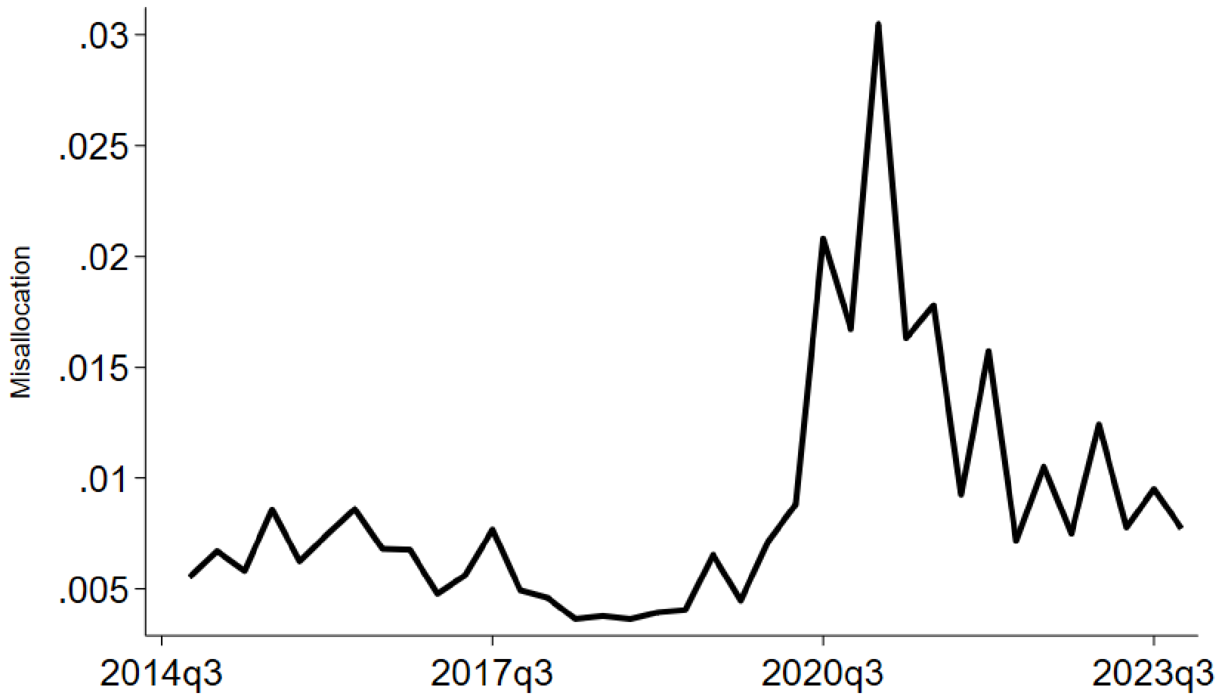

Figure 3: Cost of Misallocation

To further understand the drivers of misallocation, we decompose it into the component coming from heterogeneous cost of capital, ρ, and the component coming from heterogeneity in the agency friction. We perform two counterfactuals. In the first, we replace ρ with its average value for that quarter. This tells us how much misallocation arises from heterogeneity in the agency friction. In the second counterfactual we set the agency friction equal to its average value within the quarter, which allows us to measure the misallocation arising from heterogeneity in ρ. Note that neither counterfactual changes the within-quarter average of r^{social}, and thus the results are driven by changes in the variance of r^{social}.

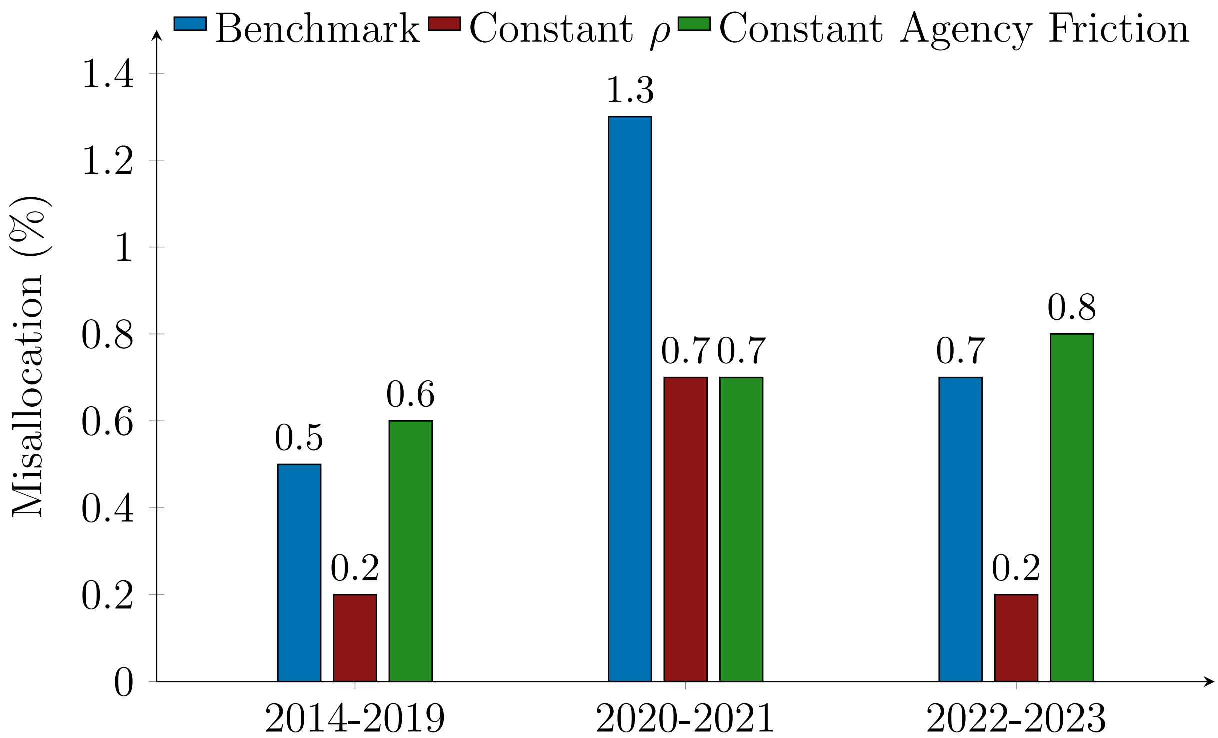

Figure 4: Decomposing Misallocation (Heterogeneity in Cost of Capital vs Agency Friction)

We show the results of these decompositions in Figure 4. Misallocation is typically driven by heterogeneity in the cost of capital, although the rise in misallocation during the pandemic is driven by an increase in the variance of the agency friction. In the pre-pandemic period, misallocation is largely a result of heterogeneous ρ: if ρ is equalized across firms then the cost of misallocation falls to just 0.2%. In contrast, the cost of misallocation in the counterfactual with a constant agency friction is slightly higher, at 0.6%, than in the benchmark case (this implies a negative covariance between the cost of capital and the agency friction). During the pandemic period (2020-2021), heterogeneity in the cost of capital and in agency frictions play a roughly equal role: the total cost of misallocation is 1.3%, while it is 0.7% in either counterfactual. In the post-pandemic period (2022-2023), heterogeneity in ρ once again plays the dominant role: misallocation would be only 0.2% in the constant ρ counterfactual.

In Appendix C, we repeat our misallocation analysis, focusing on five-year, fixed-rate loans. We find that the results are very similar to those of our main analysis.[11] This reinforces the robustness of our results, confirming that heterogeneity in the cost of capital across firms is not driven by differences in maturity or term structure.

6 Conclusion

This paper develops a novel methodology to estimate the cost of capital using credit registry microdata, and examines the implications of dispersion in the cost of capital for misallocation. We show, in a dynamic corporate finance model, the connection between the lender's cost of capital, the firm's cost of capital, and the social cost of capital, and how to measure these objects in the data. We also show how the mean and variance of the social cost of capital can be used as sufficient statistics to measure the output losses from misallocation that arise from credit market imperfections.

After developing this general methodology, we apply it to credit registry data for the United States. We find that although the cost of capital varies across firms, the resulting misallocation is modest in normal times, resulting in output losses of only 0.5%. However, dispersion in the social cost of capital among newly originated loans rose dramatically during the COVID-19 pandemic, driven by a rise in the dispersion of agency frictions. Understanding the causes of this rise in dispersion, as well as the consequences for aggregate productivity, is an important area for future research. Moreover, comparing the distribution of the cost of capital in the United States to the distribution in other economies, especially less developed economies, will help us better understand how financial markets contribute to development.

[11] In the robustness sample, there is also a brief spike in the dispersion of r^{social} earlier in the period, but it only lasts for one quarter.

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Appendix

A Proofs

Proof of Proposition 1.

$$\begin{aligned}
\mathbb{E}_t\left[\frac{\mathcal{P}_{t+1}\left(\theta+(1-\theta)\,Q_{t+1}\right)}{Q_t}\right] &= (1+\rho)\,\frac{\mathbb{E}_t\left[\mathcal{P}_{t+1}\left(\theta+(1-\theta)\,Q_{t+1}\right)\right]}{\mathbb{E}_t\left[\mathcal{P}_{t+1}\left(\theta+(1-\theta)\,Q_{t+1}\right)\right]+\mathbb{E}_t\left[\left(1-\mathcal{P}_{t+1}\right)\phi(k')/b'\right]} \\
&= (1+\rho)\left(1+\frac{\mathbb{E}_t\left[\left(1-\mathcal{P}_{t+1}\right)\phi(k')/b'\right]}{\mathbb{E}_t\left[\mathcal{P}_{t+1}\left(\theta+(1-\theta)\,Q_{t+1}\right)\right]}\right)^{-1} \\
&= (1+\rho)\,(1+\Lambda)^{-1}
\end{aligned}$$

where

$$\Lambda \equiv \frac{\mathbb{E}_t\left[\left(1-\mathcal{P}_{t+1}\right)\phi(k')/b'\right]}{\mathbb{E}_t\left[\mathcal{P}_{t+1}\left(\theta+(1-\theta)\,Q_{t+1}\right)\right]}$$

□

Proof of Proposition 3.

$$1=\sum_{t=1}^{T}\left(\frac{P}{1+\rho}\right)^{t}\left[r+\frac{(1-P)}{P}\,(1-LGD)\right]+\left(\frac{P}{1+\rho}\right)^{T}$$

Let $x=\frac{P}{1+\rho}$ so

$$1=\left(r+\frac{1-P}{P}\,(1-LGD)\right)\frac{x}{1-x}\left(1-x^{T}\right)+x^{T}$$

Guess that $1+\rho=(1+r)\,P+(1-P)\,(1-LGD)$

$$\frac{1-x}{x}=\frac{1}{x}-1=\frac{(1+r)\,P+(1-P)\,(1-LGD)}{P}-1=r+\frac{1-P}{P}\,(1-LGD)$$

And, therefore

$$1=1\left(1-x^{T}\right)+x^{T}$$

which validates the guess. □

Proof of Proposition 4.

$$
\begin{aligned}
\text{Model} \qquad \Lambda &= \frac{\mathbb{E}_t\left[\left(1-\mathcal{P}_{t+1}\right)\phi(k')/b'\right]}{\mathbb{E}_t\left[\mathcal{P}_{t+1}\left(\theta+\left(1-\theta\right)Q_{t+1}\right)\right]} \\
\text{Data} \qquad \Lambda &= \frac{\left(1-P\right)\left(1-LGD\right)}{PQ_1}
\end{aligned}
$$

The break-even condition implies

$$1+\rho = PQ_1 + \left(1-P\right)\left(1-LGD\right)$$

Hence

$$
\begin{aligned}
PQ_1 &= 1+\rho-\left(1-P\right)\left(1-LGD\right) \\
\Rightarrow \Lambda &= \frac{\left(1-P\right)\left(1-LGD\right)}{1+\rho-\left(1-P\right)\left(1-LGD\right)}
\end{aligned}
$$

□

B Data

B.1 Details on Data Cleaning and Construction

While the FR Y-14Q Schedule H.1 data goes back to 2011, we keep only data from 2014Q4 due to data quality and consistency of reporting issues.

Borrowers. We drop all loans to borrowers without a Tax Identification Number. We keep only Commercial & Industrial loans to nonfinancial U.S. addresses, i.e. lines reported on FR Y-9C equal to 3, 4, 8, 9, and 10. We drop all borrowers with NAICS codes 52 (Finance and Insurance), 92 (Public Administration), 5312 (Offices of Real Estate Agents and Brokers), and 551111 (Offices of Bank Holding Companies), as some financial companies are classified under the later two NAICS codes in our sample.

Loans. We drop all loans with a negative committed exposure, or for which the utilized exposure exceeds the committed exposure as these are likely to be mistakes. We drop all observations for which the origination date exceeds the current date, and all those for which the maturity date precedes the current date.

We keep only "vanilla" term loans (Facility type equal to 7), and we thus exclude Type A, B, and C term loans, as well as bridge term loans. We keep only loans that are classified as fixed or variable rate, and drop mixed interest rate variability loans. We keep only loans with maturity between 1 and 10 years, thus excluding very short-term and very long-term loans. We keep only loans with interest rates in the 1st-99th percentiles for fixed rate loans, and spread in the 1st-99th percentiles for variable rate loans, as some of the very high and low rates/spreads are likely to be data errors. We drop loans for which the probability of default and the loss given default are either missing or outside of the $[0, 1]$ intervals. We also drop loans for which the probability of default is equal to 1, as that is an indicator that the loan is in default.

C Robustness: Results for Fixed-Rate Five-Year Loans

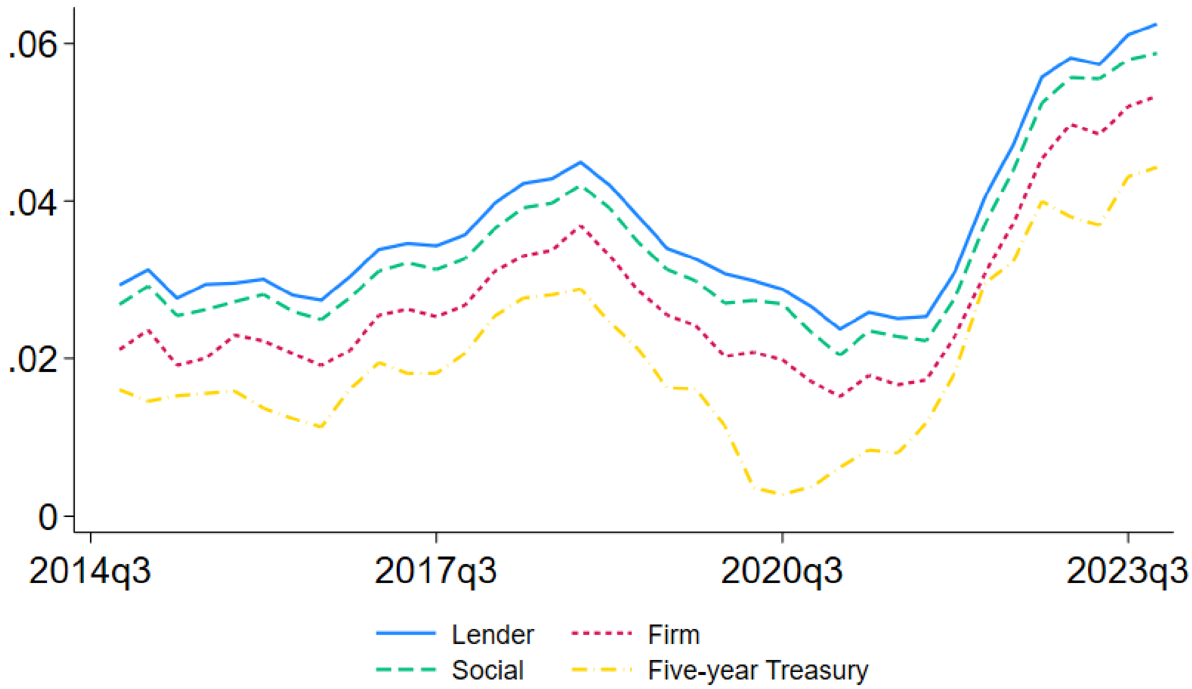

Figure 5: Averages by Quarter of Origination (Fixed-Rate Five-Year Sample)

Figure 6: Cost of Misallocation (Fixed-Rate Five-Year Sample)

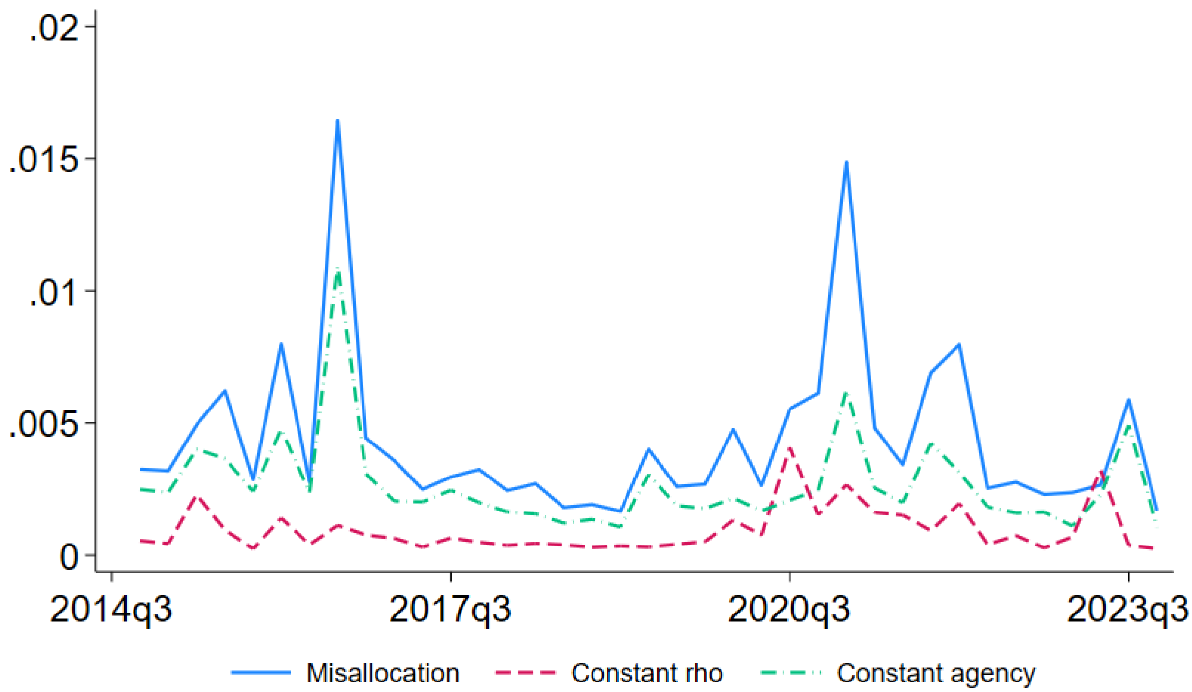

Figure 7: Decomposing Misallocation (Fixed-Rate Five-Year Sample)