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Evidence from the Dispersion in Borrowing Costs**

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Misallocation and Financial Market Frictions: Some Direct Evidence from the Dispersion in Borrowing Costs

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Abstract

Financial market frictions distort the allocation of resources among productive units—all else equal, firms whose financing choices are affected by financial frictions face higher borrowing costs than firms with ready access to capital markets. As a result, input choices may differ systematically across firms in ways that are unrelated to their productive efficiency. We propose a simple accounting framework that allows us to assess the empirical magnitude of the loss in aggregate resources due to such misallocation. To a second-order approximation, our accounting framework requires only information on the dispersion in borrowing costs across firms. We measure firm-specific borrowing costs for a subset of U.S. manufacturing firms directly from the interest rate spreads on their outstanding publicly-traded debt. Given the observed variation in borrowing costs, our approximation method implies a relatively modest loss in efficiency due to resource misallocation—on the order of 1 to 2 percent of measured total factor productivity (TFP). According to our accounting framework, the correlation between firm size and borrowing costs is irrelevant under the assumption that financial distortions and firm-level efficiency are jointly log-normally distributed. To take into account the effect of covariation between firm size and borrowing costs, we also consider a more general framework that dispenses with the assumption of log-normality and which yields somewhat higher estimates of the resource losses—about 3.5 percent of measured TFP. Counterfactual experiments indicate that dispersion in borrowing costs must be an order of magnitude higher than that observed in the U.S. financial data, in order for misallocation—arising from financial distortion—to account for a significant fraction of measured TFP differentials across countries.

JEL CLASSIFICATION: D92, O16, O40

KEYWORDS: total factor productivity, financial distortions, firms-specific borrowing costs

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1 Introduction

Economists have long emphasized that micro-level distortions can have large adverse effects on aggregate productivity (cf. Hopenhayn and Rogerson [1993] and Guner et al. [2008]). Relatedly, Restuccia and Rogerson [2008] have argued that systematic and persistent differences in the allocation of resources across production units of varying productivity may be an important determinant of differences in income per capita across countries, a hypothesis that seems to be borne out by the data. For example, using detailed microdata on manufacturing establishments in China and India, Hsieh and Klenow [2009] estimate that resource misallocation accounts for 30 to 60 percent of the difference between the total factor productivity (TFP) in U.S. manufacturing and the corresponding sectoral TFP in China and India.¹

In light of the enormous differences in the depth and sophistication of financial markets across developed and developing countries, a large literature has long stressed the role of finance in economic development; see Matsuyama [2007] for a comprehensive review. More recently, Amaral and Quintin [2010], Greenwood et al. [2010], and Buera et al. [2011] have developed theoretical models, which show—in a quantitative sense—that a large portion of cross-country differences in TFP may be attributable to resource misallocation arising from imperfect financial markets. Although the nature of financial market imperfections differs across their theoretical frameworks, their quantitative analysis shares a common thread, in the sense that the results are obtained by choosing the model parameters to match the size distribution of firms in an environment where financial distortions determine firm size.²

In a recent paper, Midrigan and Xu [2010] challenge these findings. Like Buera et al. [2011], Midrigan and Xu [2010] consider a model in which firms facing financing constraints have a strong incentive to self-finance through forward-looking savings behavior. However, when they calibrate the model to match both the size distribution of firms and the volatility of sales growth, there is simply too little variability in the observed growth of sales to generate quantitatively important differences in the cost of capital across firms. The implication of this result is that financial distortions account for at most 5 percent of the difference in manufacturing TFP between Columbia and South Korea, the latter being a benchmark country with highly developed capital markets.

Although obtaining very different conclusions, the aforementioned studies share a common analytical approach—that is, they identify the size of TFP losses due to resource misallocation using information on the distribution of sales across establishments and over time. In this paper, we provide a direct measure of financial distortions based on the observed differences in borrowing

¹As shown by Klenow and Rodríguez-Clare [1997] and Hall and Jones [1999] differences in income per capita across countries are primarily accounted for by low TFP in poorer countries.

²Financial frictions in Amaral and Quintin [2010] are due to the limited enforcement of contracts, while Greenwood et al. [2010] embed a costly-state verification framework into a standard neoclassical growth model. Buera et al. [2011] also introduce financial frictions vis-à-vis imperfect enforceability of contracts, but in an important extension, they also allow the entrepreneurs to overcome credit constraints over time through self-financing.

costs across firms. Specifically, we develop an accounting framework in which observed differences in borrowing costs across firms can be mapped into measures of aggregate resource misallocation that may plausibly be attributed to financial market frictions. Using a log-normal approximation, we show that the extent of resource misallocation can be inferred from cross-industry or cross-country information on the dispersion in borrowing costs.

We apply our accounting framework to a panel of U.S. manufacturing firms drawn from the Compustat database. Despite fairly large and persistent differences in borrowing costs across firms, our estimates imply relatively modest losses in TFP owing to resource misallocation—roughly on the order of 3.5 percent of TFP in the U.S. manufacturing sector. Our results can be obtained directly from the log-normal approximation and information on the dispersion of interest rates across firms. Nonetheless, our methodology also allows us to relax the log-normal approximation and infer TFP losses using the joint distribution of sales and borrowing costs. We find that the estimated losses under this approach closely match those obtained under the assumption of log-normality. This finding demonstrates both the robustness of our results, and its applicability to a broader environment where firm-level data on the joint distribution of sales and borrowing costs may not be readily available.

2 Borrowing Costs and Firm Size: Some Some Stylized Facts

In this section, we briefly describe our unique data set on firm-level borrowing costs and present some stylized facts about the relationship between the cross-sectional dispersion in borrowing costs and firm size.

2.1 Data Description

Our main analysis focuses on a subset of U.S. manufacturing firms, whose distinguishing characteristic is that they have access to the corporate bond market. For a panel of such firms covered by the S&P's Compustat and the Center for Research in Security Prices (CRSP), we obtained month-end secondary market prices of their outstanding securities from the Lehman/Warga and Merrill Lynch databases.³ To ensure that we are measuring borrowing costs of different firms at the same point in their capital structure, we limited our sample to senior unsecured issues with a fixed coupon schedule only.

Using the secondary market prices of individual securities, we construct the corresponding credit spreads—measured relative to risk-free Treasury rates—based on the methodology described in Gilchrist and Zakrajšek [2011]. To ensure that our results are not driven by a small number of extreme observations, we eliminated all observations with credit spreads below 5 basis points and

³These two data sources include secondary market prices for a vast majority of dollar-denominated bonds publicly issued in the U.S. corporate cash market; see Gilchrist et al. [2009] for details.

Table 1: Selected Corporate Bond Characteristics

Variable	Mean	SD	Min	P50	Max
No. of bonds per firm/month	2.86	3.04	1.00	2.00	52.0
Mkt. value of issue (\$mil.) ^a	358.9	360.1	1.22	260.4	5,628
Maturity at issue (yrs.)	12.8	9.2	1.0	10.0	40.0
Term to maturity (yrs.)	10.8	8.5	1.0	7.7	30.0
Duration (years)	6.42	3.36	0.92	5.92	15.8
Credit rating (S&P)	-	-	D	A3	AAA
Coupon rate (pct.)	7.06	1.97	1.70	6.85	15.25
Nominal effective yield (pct.)	6.80	2.20	0.46	6.71	19.89
Credit spread (bps.)	170	157	5	116	1,000

NOTE: Sample period: 1985:M1–2010:M12; Obs. = 141,770; No. of bonds = 2,623; No. of firms = 497. Sample statistics are based on trimmed data (see text for details).

^a Market value of the outstanding issue deflated by the CPI (2005 = 100).

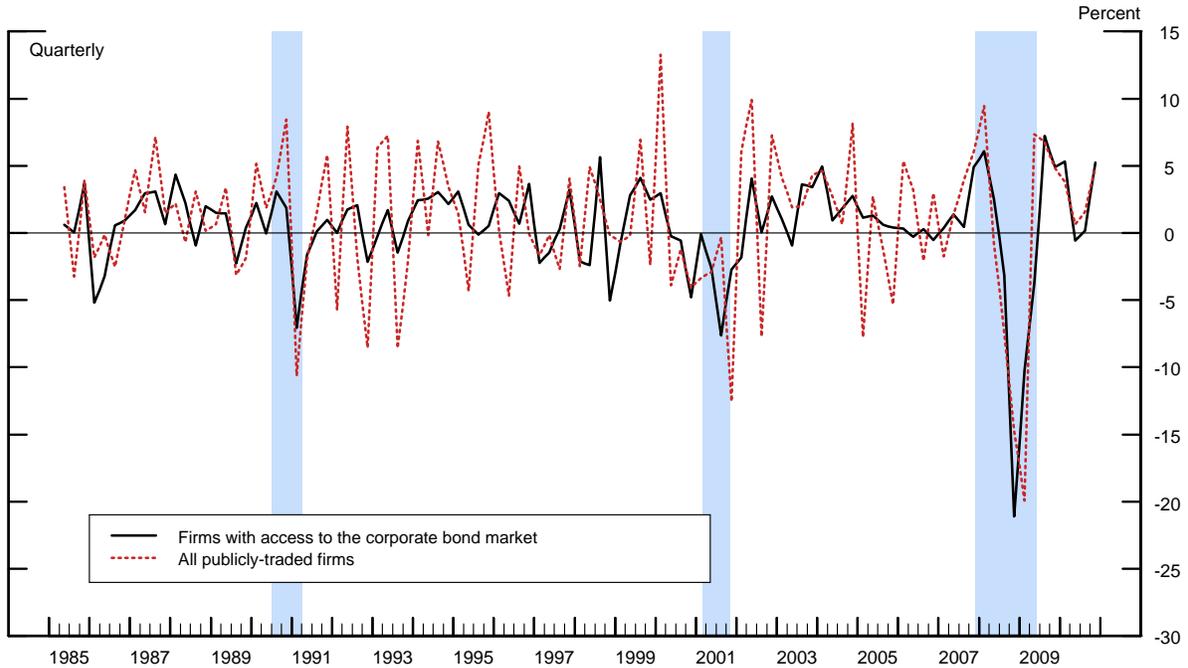
greater than 1,000 basis points, cutoffs corresponding roughly to the 2.5th and 97.5th percentiles of the credit spread distribution, respectively. In addition, we eliminated from our sample very small corporate issues (par value of less than \$1 million) and all observations with a remaining term-to-maturity of less than one year or more than 30 years. These selection criteria yielded a sample of 2,623 individual securities over the 1985:M1–2010:M12 period. We matched these corporate securities with their issuer’s quarterly income and balance sheet data from Compustat and daily data on equity valuations from CRSP, a procedure that yielded a matched sample of 497 firms, split about equally between durable and nondurable goods manufacturing industries.

Table 1 contains summary statistics for the key characteristics of bonds in our sample. Note that a typical firm in our sample has only a few senior unsecured issues outstanding at any point in time—the median firm, for example, has two such issues trading in any given month. This distribution, however, exhibits a significant positive skew, as some firms can have many more issues trading in the secondary market at a point in time. To calculate a *firm-specific* credit spread in any given month, we simply average the spreads on the firm’s outstanding bonds in that month.⁴

The distribution of the market values of these issues is similarly skewed, with the range running from \$1.2 million to more than \$5.6 billion. The maturity of these debt instruments is fairly long, with the average maturity at issue of almost 13 years; the average remaining term-to-maturity in our sample is 10.84 years. In terms of default risk—at least as measured by the S&P credit ratings—our sample spans the entire spectrum of credit quality, from “single D” to “triple A.” At “A3,” however, the median observation is still solidly in the investment-grade category. An average bond has an expected return of 170 basis points above the comparable risk-free rate, while the standard deviation of 157 basis points reflects the wide range of credit quality in our sample.

⁴As a robustness check, we also computed firm-specific spreads as a weighted average of credit spreads on the firm’s outstanding bonds, with weights equal to the market value of each issue. The resulting credit spreads and all the results were essentially identical.

Figure 1: Growth of Real Sales in U.S. Manufacturing



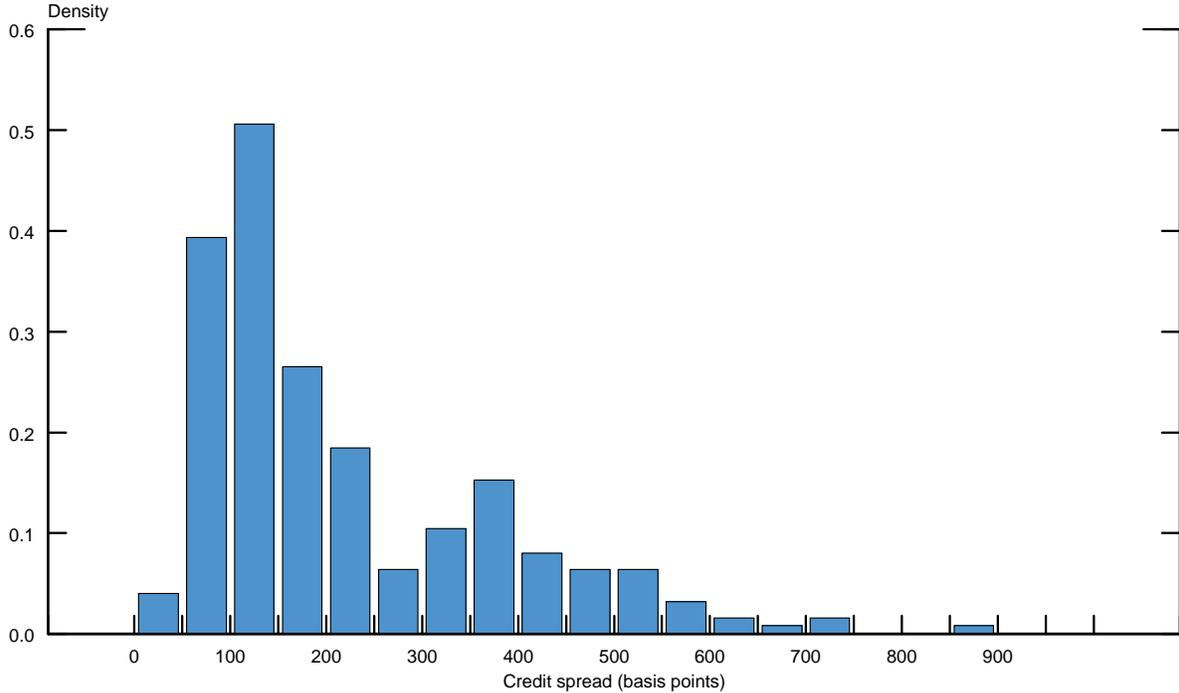
NOTE: Sample period: 1985:Q1–2010:Q4. The solid line depicts the quarterly growth rate of real sales for our sample of 497 manufacturing firms that have access to the corporate bond market; the dotted line depicts the growth rate of real sales for all publicly-traded U.S. manufacturing firms in Compustat. The nominal sales are deflated by the implicit price deflator for the nonfarm business sector output (2005 = 100); all data are seasonally adjusted. The shaded vertical bars represent the NBER-dated recessions.

We focus on the 1985–2010 period because it is characterized by a growing tendency for U.S. corporate borrowing to take the form of negotiable securities issued directly in capital markets. The resulting deepening of the corporate bond market has led to a substantial degree of disintermediation, as well as to the development of well-functioning markets in derivatives, in which credit, interest rate, and currency risks, for example, can be readily hedged. Importantly, a full-fledged corporate bond market tends to be associated with sound financial reporting systems, a thriving community of professional financial analysts, multiple credit rating agencies, a wide range of corporate debt instruments demanding sophisticated credit analysis, and efficient procedures for corporate reorganization and liquidation, factors that greatly facilitate the process of price discovery for corporate debt claims.⁵ Indeed, a well-developed corporate bond market is in a much better position than the banking system—which is heavily leveraged and subject to regulatory imperfections—to exert a crucial disciplinary role exercised by market forces.⁶ As a result, the

⁵For example, using high-frequency bond transaction prices of U.S. firms, Hotchkiss and Ronen [2002] find that the informational efficiency of corporate bond prices is similar to that of the underlying stocks.

⁶As shown by Hakansson [1982], the financial system with a well-developed bond market will—under fairly general

Figure 2: Distribution of Firm-Level Borrowing Costs



NOTE: The histogram depicts the distribution of firm-specific average credit spreads for our sample of 497 manufacturing firms.

variation in our firm-specific interest rates likely reflects the dispersion in “true” borrowing costs both across firms and over time.

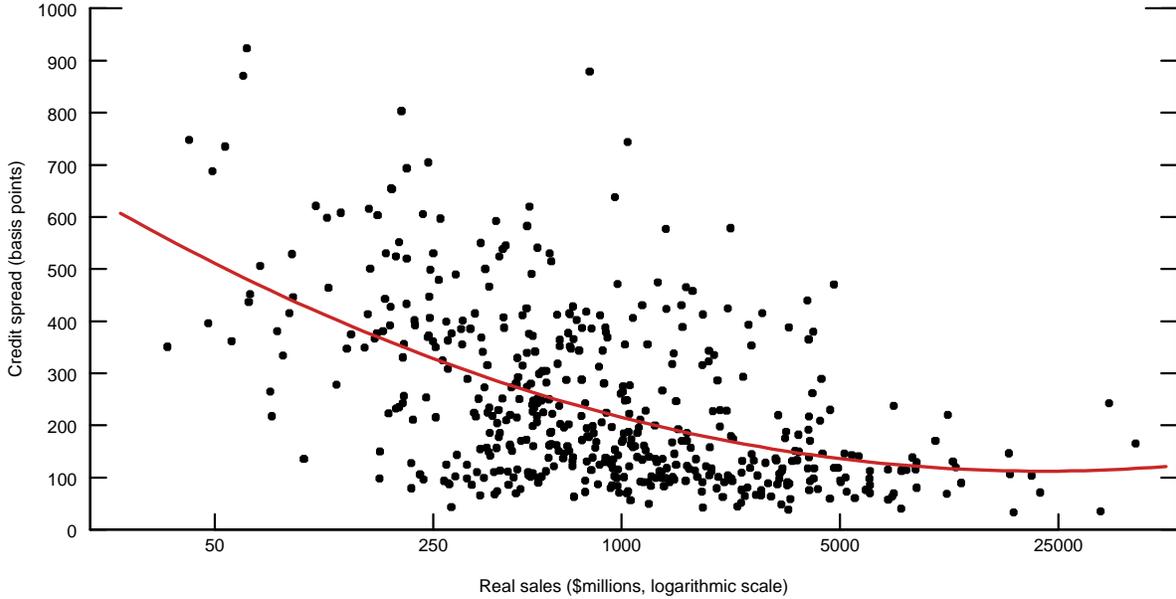
Although our sample is restricted to manufacturing firms with the access to the corporate bond market, these 497 firms account, on average, for about 50 percent of total sales in U.S. manufacturing over the 1985–2010 period. Moreover, as shown in Figure 1, the cyclical fluctuations in their sales closely match the growth of sales of all publicly-traded manufacturing firms in the Compustat database. In combination with the fact that our sample of firms spans a wide range of credit quality (see Table 1), these features of the data suggest that the dispersion in borrowing costs for this subset of firms is likely representative of the manufacturing sector as a whole.

2.2 Firm-Level Borrowing Costs and Firm Size

To get a sense of the cross-sectional dispersion in firm-level borrowing costs, we calculate the average credit spread for each firm over time, a measure of debt financing costs that abstracts from the substantial cyclical variation that characterizes credit spreads at business cycle frequencies. The

conditions—Pareto-dominate a financial system in which banks do most of the lending.

Figure 3: Firm-Level Borrowing Costs and Firm Size



NOTE: The scatter plot depicts the relationship between firm-specific average credit spreads and average firm size, as measured by real sales, for our sample of 497 manufacturing firms. The nominal sales are deflated by the implicit price deflator for the nonfarm business sector output (2005 = 100).

resulting distribution is shown in Figure 2. The central tendency of the distribution—as measured by its mean—is 240 basis points, while its standard deviation is about 160 basis points. Recall that this specific sample trims the upper tail of the distribution of credit spreads at 1,000 basis points, so the standard deviation of 160 basis points likely underestimates the true dispersion of credit spreads across firms to a certain extent.

We now turn to the relationship between firm size and credit spreads. In Figure 3, we plot the average credit spread for each firm over time against the average firm size as measured by real sales. The fact that we are averaging over time implies that this relationship is capturing the long-term relationship between firm size and borrowing costs in the U.S. manufacturing sector. The solid line shows the fitted values from regressing the firm-specific average credit spread on a second-order polynomial function of the logarithm of real sales, which highlights the strong negative relationship between firm size and borrowing costs observable in the data.

Credit spreads capture both the likelihood of default and a residual component that relates to firm-specific factors such as loss given default and pricing terms reflecting individual firm characteristics.⁷ The likelihood of default is intimately related to leverage of the firm. Thus, to the extent

⁷In the corporate finance literature, there is a well-known result—the “credit spread puzzle”—which shows that less than one-half of the variation in corporate bond credit spreads can be attributed to the financial health of the issuer (e.g., Elton et al. [2001]). As shown by Collin-Dufresne et al. [2001], Houwelling et al. [2005], Driessen [2005],

that smaller firms are more leveraged, they will be considered by investors as being of lower credit quality and thus face higher spreads in the debt markets.

To control for differences in default risk across firms, we estimate the following regression:

$$s_{it} = \beta_1 DD_{it} + \beta_2 DD_{it}^2 + \lambda_t + \epsilon_{it},$$

where s_{it} denotes the credit spread of firm i in month t , DD_{it} is the *distance-to-default* for firm i , and λ_t is the time fixed effect. The key feature of the above specification is that the firm-specific (time-varying) default risk is captured by the distance-to-default (DD), a market-based indicator of credit risk based on the contingent claims framework developed in the seminal work of Merton [1974]. Briefly, this option-theoretic approach assumes that a firm has just issued a single zero-coupon bond of face value F that matures at date T . Rational stockholders will default at date T only if the total value of the firm $V_T < F$; by assumption, the rights of the bondholders are activated only at the maturity date, as stockholders will maintain control of the firm even if the value of the firm $V_s < F$ for some $s < T$. Under the assumptions of the model, the probability of default—that is, $\Pr[V_T < F]$ —depends on the distance-to-default, a volatility-adjusted measure of leverage inferred from equity valuations and the firm’s observed capital structure.⁸

The regression fits the data quite well, explaining 55 percent of the variation in firm-specific credit spreads. In Figure 4, we plot the firm-specific average residual credit spread (i.e., $\sum_{t=1}^{T_i} \hat{\epsilon}_{it}$) against the average firm size. Although the dispersion in credit spreads is reduced noticeably once default risk is taken into account, we nevertheless still find a strong negative relationship between the non-default component of credit spreads and firm size. Such permanent differences in borrowing costs across firms imply that financial distortions play a potentially important role in the misallocation of resources across firms.

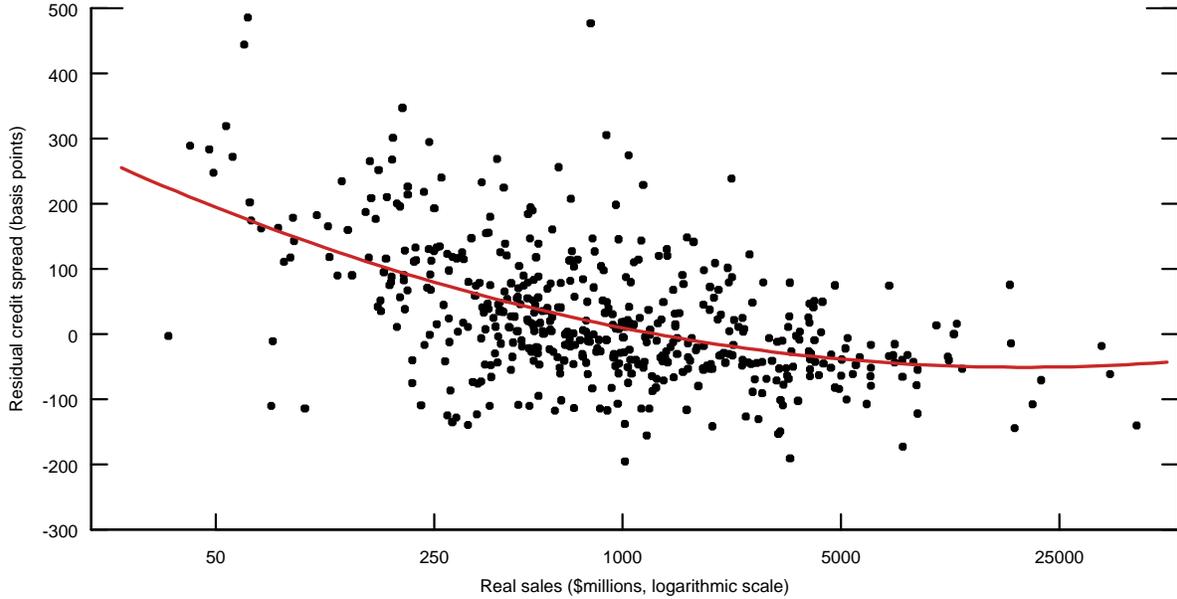
3 The TFP Accounting Framework

In this section, we present the accounting framework that relates losses in TFP due to resource misallocation to dispersion in firm-specific borrowing costs. Our procedure is derived from the decreasing returns to scale production framework outlined in Midrigan and Xu [2010]; it is also directly related to the TFP accounting procedure emphasized by Hsieh and Klenow [2009].

and Duffie et al. [2007], the unexplained portion of the variation in credit spreads appears to reflect some combination of time-varying liquidity premium, to some extent the tax treatment of corporate bonds, and a default-risk factor.

⁸In addition to being used widely by the financial industry, our choice of the Merton DD-framework is also motivated by the work of Schaefer and Strebulaev [2008], who present compelling micro-level evidence showing that the DD-model accounts well for the default-risk component of corporate bond prices. To calculate the DDs for our sample of firms, we employ a robust procedure developed by Bharath and Shumway [2008].

Figure 4: Residual Credit Spreads and Firm Size



NOTE: The scatter plot depicts the relationship between firm-specific average residual credit spreads and average firm size, as measured by real sales, for our sample of 497 manufacturing firms. The nominal sales are deflated by the implicit price deflator for the nonfarm business sector output (2005 = 100).

3.1 The Production Environment

We assume that firms (indexed by i) employing capital (K) and labor (L) have access to a decreasing returns to scale production function of the form:

$$Y_i = A_i^{1-\eta} (K_i^{1-\alpha} L_i^\alpha)^\eta,$$

where $0 < \eta < 1$ is the degree of decreasing returns in production and A_i is a firm-specific level of productivity. Decreasing returns may be due to the managerial span of control as in Lucas [1978] or, alternatively, due to monopolistic competition in an environment with Dixit-Stiglitz preferences over heterogeneous goods.

We further assume that firms must borrow at a firm-specific interest rate r_i in order to obtain both capital and labor inputs. Letting $0 < \delta < 1$ denote the rate of capital depreciation and W the aggregate wage, the optimal choice of inputs implies that firms equate the marginal revenue products of capital and labor to their respective costs:

$$\begin{aligned} (1 - \alpha)\eta \frac{Y_i}{K_i} &= r_i + \delta; \\ \alpha\eta \frac{Y_i}{L_i} &= (1 + r_i)W, \end{aligned}$$

where the second equation captures the fact that we assume that labor costs reflect borrowing costs as well as the aggregate wage.

In this framework, the optimal capital-labor ratio is given by

$$\frac{K_i}{L_i} = \frac{1 - \alpha}{\alpha} \left[\frac{(1 + r_i)W}{r_i + \delta} \right].$$

Solving for the labor input yields

$$\frac{[(1 + r_i)W]}{\alpha\eta} L_i = A_i^{1-\eta} \left[\frac{1 - \alpha}{\alpha} \left(\frac{(1 + r_i)W}{r_i + \delta} \right) L_i \right]^{(1-\alpha)\eta} L_i^{\alpha\eta},$$

which implies the optimal input choices:

$$\begin{aligned} L_i &= c_1 A_i \left[(1 + r_i)^{-\frac{1-(1-\alpha)\eta}{1-\eta}} (r_i + \delta)^{-\frac{(1-\alpha)\eta}{1-\eta}} \right]; \\ K_i &= c_2 A_i \left[(1 + r_i)^{-\frac{\alpha\eta}{1-\eta}} (r_i + \delta)^{-\frac{1-\alpha\eta}{1-\eta}} \right], \end{aligned}$$

for some positive constants c_1 and c_2 .

Letting

$$w_i^l \equiv \left[(1 + r_i)^{-\frac{1-(1-\alpha)\eta}{1-\eta}} (r_i + \delta)^{-\frac{(1-\alpha)\eta}{1-\eta}} \right]; \quad (1)$$

$$w_i^k \equiv \left[(1 + r_i)^{-\frac{\alpha\eta}{1-\eta}} (r_i + \delta)^{-\frac{1-\alpha\eta}{1-\eta}} \right], \quad (2)$$

then optimal input choices are proportional to firm-level productivity adjusted for firm-specific differences in factor input costs:

$$\begin{aligned} L_i &= c_1 A_i w_i^l; \\ K_i &= c_2 A_i w_i^k. \end{aligned}$$

In this context, w_i^l and w_i^k denote labor and capital “wedges,” respectively, which induce distortions in input choices relative to an efficient allocation of inputs. The efficient allocation of inputs across firms is determined by setting $w_i^l = w^l$ and $w_i^k = w^k$ for all i .

3.2 Aggregation and TFP

Define aggregate labor and capital inputs according to

$$L = c_1 \int A_i w_i^l di \quad \text{and} \quad K = c_2 \int A_i w_i^k di,$$

and define the wedge in the cost index as

$$w_i = (w_i^l)^\alpha (w_i^k)^{1-\alpha}.$$

The aggregate output may then be expressed as

$$Y = \int Y_i di = c_1^{\alpha\eta} c_2^{(1-\alpha)\eta} \int A_i w_i^\eta di.$$

Total factor productivity is measured as aggregate output relative to a geometrically-weighted average of aggregate labor and capital inputs:

$$TFP = \frac{Y}{L^{\alpha\eta} K^{(1-\alpha)\eta}} = \frac{\int A_i w_i^\eta di}{(\int A_i w_i^l di)^{\alpha\eta} (\int A_i w_i^k di)^{(1-\alpha)\eta}},$$

or in logs,

$$\log(TFP) = \log\left(\int A_i w_i^\eta di\right) - \alpha\eta \log\left(\int A_i w_i^l di\right) - (1-\alpha)\eta \left(\int A_i w_i^k di\right). \quad (3)$$

Assuming that A_i , w_i^l , and w_i^k are jointly distributed according to a log-normal distribution,

$$\begin{bmatrix} \log A_i \\ \log w_i^l \\ \log w_i^k \end{bmatrix} \sim \text{MVN} \left(\begin{bmatrix} a \\ w_l \\ w_k \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{a,w_l} & \sigma_{a,w_k} \\ \sigma_{a,w_l} & \sigma_{w_l}^2 & \sigma_{w_l,w_k} \\ \sigma_{a,w_k} & \sigma_{w_l,w_k} & \sigma_{w_k}^2 \end{bmatrix} \right),$$

then the second-order approximations of the three terms in equation (3) are given by

$$\begin{aligned} \log\left(\int A_i w_i^\eta di\right) &= a + \eta[\alpha w_l + (1-\alpha)w_k] + \frac{1}{2}\sigma_a^2 + \frac{\eta^2\alpha^2}{2}\sigma_{w_l}^2 + \frac{\eta^2(1-\alpha)^2}{2}\sigma_{w_k}^2 \\ &\quad + \eta\alpha(1-\alpha)\sigma_{w_l,w_k} + \eta[\alpha\sigma_{w_l,a} + (1-\alpha)\sigma_{w_k,a}]; \\ \log\left(\int A_i w_i^l di\right) &= a + w_l + \frac{1}{2}\sigma_a^2 + \frac{1}{2}\sigma_{w_l}^2 + \sigma_{w_l,a}; \\ \log\left(\int A_i w_i^k di\right) &= a + w_k + \frac{1}{2}\sigma_a^2 + \frac{1}{2}\sigma_{w_k}^2 + \sigma_{w_k,a}. \end{aligned}$$

Combining the above expressions and rearranging yields the second-order approximation of equation (3)

$$\begin{aligned} \log(TFP) &= (1-\eta) \left[a + \frac{1}{2}\sigma_a^2 \right] + \frac{\eta\alpha(1-\eta\alpha)}{2}\sigma_{w_l}^2 + \frac{\eta(1-\alpha)(1-\eta(1-\alpha))}{2}\sigma_{w_k}^2 \\ &\quad - \eta^2\alpha(1-\alpha)\text{Corr}(w_l, w_k)\sigma_{w_l}\sigma_{w_k}. \end{aligned} \quad (4)$$

In an economy with an efficient allocation of resources, w_i^k and w_i^l are constant (i.e., $w_i^l = w^l$

and $w_i^k = w^k$ for all i). In those circumstances, equation (4) reduces to

$$\log(TFP_E) = (1 - \eta) \left[a + \frac{1}{2} \sigma_a^2 \right].$$

Hence, the relative TFP loss due to resource misallocation is given by

$$\log \left(\frac{TFP}{TFP_E} \right) = \frac{\eta \alpha (1 - \eta \alpha) \sigma_{w_l}^2}{2} + \frac{\eta (1 - \alpha) (1 - \eta (1 - \alpha)) \sigma_{w_k}^2}{2} - \eta^2 \alpha (1 - \alpha) \text{Corr}(w_l, w_k) \sigma_{w_l} \sigma_{w_k}. \quad (5)$$

Several comments about equation (5) are in order. First, the TFP loss due to resource misallocation is an increasing function of the dispersion in the labor and capital wedges σ_{w_l} and σ_{w_k} , respectively. Second, up to a second-order (log-normal) approximation, the covariance between firm-level TFP and the capital and labor wedges is irrelevant for the size of the TFP loss due to misallocation. Thus, up to a second-order approximation, size-based distortions matter only to the extent that they create dispersion in the labor and capital wedges and not because they are based on size per se. And lastly, holding dispersion in the labor and capital wedges fixed, a high correlation between the labor and capital wedges reduces the relative TFP loss due to resource misallocation.

3.3 Resource Misallocation and Dispersion in Interest Rates

To derive an approximate relationship between the dispersion in interest rates and TFP losses due to the misallocation of resources, we first consider a case in which both the labor and capital input choices are fully distorted by financial market frictions (i.e., capital input costs are $r_i + \delta$ and labor input costs are given by $(1 + r_i)W$). In that case, $\text{Corr}(w_l, w_k) = 1$, and the log-labor and log-capital wedges are given by

$$\begin{aligned} \log w_i^l &= -\frac{1 - (1 - \alpha)\eta}{1 - \eta} \log(1 + r_i) - \frac{(1 - \alpha)\eta}{1 - \eta} \log(r_i + \delta); \\ \log w_i^k &= -\frac{\alpha\eta}{1 - \eta} \log(1 + r_i) - \frac{1 - \alpha\eta}{1 - \eta} \log(r_i + \delta). \end{aligned}$$

The first-order approximations of the log wedges around $\log(r_i)$ are then given by

$$\begin{aligned} \log w_i^l &\approx -\frac{1}{1 - \eta} \left[(1 - (1 - \alpha)\eta) \frac{r}{1 + r} + \alpha\eta \frac{r}{r + \delta} \right] \log(r_i); \\ \log w_i^k &\approx -\frac{1}{1 - \eta} \left[\alpha\eta \frac{r}{1 + r} + (1 - \alpha\eta) \frac{r}{r + \delta} \right] \log(r_i). \end{aligned}$$

Thus, the ratio of the standard deviation of the labor wedge relative to the capita wedge can be approximated as

$$\frac{\sigma_{w_l}}{\sigma_{w_k}} \approx \frac{[(1 - (1 - \alpha)\eta)(r^2 + r\delta) + (1 - \alpha)\eta(r + r^2)]}{[\alpha\eta(r^2 + r\delta) + (1 - \alpha\eta)(r + r^2)]}.$$

Because the terms involving r^2 and $r\delta$ are an order of magnitude smaller than the terms involving r , a rough approximation implies that

$$\frac{\sigma_{w_l}}{\sigma_{w_k}} \approx \frac{(1 - \alpha)\eta}{1 - \alpha\eta}.$$

Using this result, we can approximate the expression for the relative TFP loss as a function of $\sigma_{w_k}^2$ as

$$\begin{aligned} \log\left(\frac{TFP}{TFP_E}\right) &= \left[\frac{\eta(1 - \alpha)[1 - \eta(1 - \alpha)]}{2} + \frac{\eta\alpha(1 - \alpha\eta)}{2} \left(\frac{(1 - \alpha)\eta}{1 - \alpha\eta}\right)^2 \right. \\ &\quad \left. - \eta^2\alpha(1 - \alpha)\frac{(1 - \alpha)\eta}{1 - \alpha\eta} \right] \sigma_{w_k}^2, \end{aligned} \quad (6)$$

where

$$\sigma_{w_k} = \frac{1}{1 - \eta} \left[\alpha\eta \frac{r}{1 + r} + (1 - \alpha\eta) \frac{r}{r + \delta} \right] \sigma_{\log(r)}.$$

The first term in equation (7) reflects the direct effect of variation in w_k on the resource misallocation. The second term captures the direct effect of variation in w_l , while the third term is due to the covariance between w_l and w_k . Combining the last two terms implies that their net effect on the relative TFP loss is negative:

$$\log\left(\frac{TFP}{TFP_E}\right) = \left[\frac{\eta(1 - \alpha)[1 - \eta(1 - \alpha)]}{2} - \frac{\eta\alpha(1 - \alpha\eta)}{2} \frac{\sigma_{w_l}^2}{\sigma_{w_k}^2} \right] \sigma_{w_k}^2. \quad (7)$$

It is useful to contrast the result in equation (7) with the case where financial market frictions distort only the choice of the capital input, rather than both the capital and labor inputs. In this case, $\sigma_{w_l} = 0$, and the TFP loss due to resource misallocation is given by

$$\log\left(\frac{TFP}{TFP_E}\right) = \frac{\eta(1 - \alpha)[1 - \eta(1 - \alpha)]}{2} \sigma_{w_k}^2, \quad (8)$$

where

$$\sigma_{w_k} = \left[\frac{(1 - \alpha\eta)}{1 - \eta} \right] \left[\frac{r}{r + \delta} \right] \sigma_{\log(r)}.$$

Note that for a given σ_{w_k} , the TFP loss in the case of no labor input distortions is strictly greater than the loss with labor input distortions that are perfectly correlated with the distortions in the capital input. Distortions in the labor input increase the variability of σ_{w_k} by the amount $\left(\frac{\alpha\eta}{1 - \eta}\right) \left(\frac{r}{1 + r}\right) \sigma_{\log(r)}$. However, because the term $r/(1 + r)$ is relatively small, the effect on the

variability of σ_{w_k} is significantly attenuated. As a result, it is still likely the case that the relative TFP loss in the economy where financial frictions distort only the choice of capital inputs is greater than the TFP loss in the economy in which both inputs are distorted, even after taking into account the effect of omitting the impact of labor input distortions on σ_{w_k} . In the event that financial market frictions have no effect on the labor market, equation (8) provides a useful approximation to the loss of TFP due resource misallocation. In addition, it likely provides an upper bound for TFP losses even if financial market frictions directly distort the firm’s choice of the labor input.

4 Results

In this section, we use our framework to provide some estimates of TFP losses for the U.S. manufacturing sector implied by resource misallocation arising from financial market frictions. Specifically, we use the information on the dispersion of firm-specific borrowing costs to calculate the implied TFP loss, an approach that relies on the assumption of log-normality when computing the second-order approximation of the relative TFP loss. By utilizing the corresponding information on firm-level sales, we show that this approximation provides a reasonable estimate of TFP losses due to resource misallocation.

In our analysis, we assume that the firm-specific borrowing costs in quarter t —denoted by r_{it} —are equal to the real risk-free long-term interest rate r_t^* plus the firm-specific premium given by the credit spread s_{it} :⁹

$$r_{it} = r_t^* + s_{it}.$$

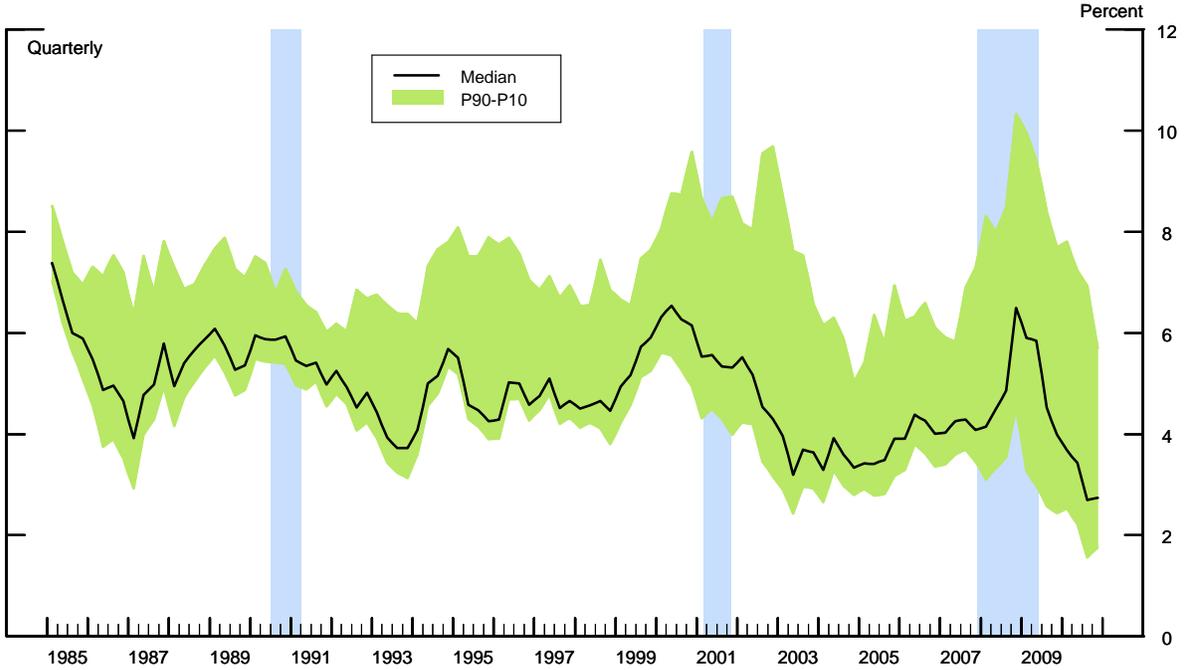
For the real risk-free rate r_t^* , we use the difference between the 10-year nominal Treasury yield and the average expected CPI inflation over the next 10 years, as measured by the Philadelphia Fed’s Survey of Professional Forecasters. In all exercises, we set the depreciation rate $\delta = 0.06$, the labor share $\alpha = 2/3$, and the degree of decreasing returns to scale $\eta = 0.85$, values that are standard in the literature.

Figure 5 depicts the time-series evolution of the cross-sectional distribution of real interest rates for our sample of manufacturing firms with access to the corporate bond market. The shaded band around the median real interest rate (the solid line) depicts the 90th and 10th percentiles of the distribution of borrowing costs at each point in time. Over the 1985–2010 period, the P90–P10 range has fluctuated in the range between 140 basis and 670 basis points, an indication of a significant dispersion in firm-level borrowing costs.

According to our accounting framework, we can infer $\log w_i^l$ and $\log w_i^k$ for each firm in our sample using equations (1) and (2) and the average firm-specific real interest rate r_i . Given these wedges, we can compute their respective standard deviations σ_{w_l} and σ_{w_k} . Using equation (5), we can then calculate the implied TFP loss due to resource misallocation arising from financial market

⁹Quarterly credit spread s_{it} is calculated as a simple average of the corresponding monthly credit spreads.

Figure 5: Dispersion of Firm-Level Borrowing Costs in U.S. Manufacturing



NOTE: Sample period: 1985:Q1–2010:Q4. The solid line depicts the median of real interest rates for our sample of 497 manufacturing firms that have access to the corporate bond market; the shaded band depicts the corresponding P90–P10 range. The shaded vertical bars represent the NBER-dated recessions.

frictions.

The above procedure relies only on the cross-sectional dispersion in real interest rates to compute TFP losses due resource misallocation. Given data on firm-level (real) sales—denoted by Y_{it} —and firm-specific interest rates, it is possible to infer directly the implied capital and labor inputs, according to

$$L_{it} = \frac{\alpha \eta Y_{it}}{(1 + r_{it})W} \quad \text{and} \quad K_{it} = \frac{(1 - \alpha) \eta Y_{it}}{r_{it} + \delta}.$$

Summing over sales and the implied inputs yields

$$Y = \frac{1}{NT} \sum_i \sum_t Y_{it}, \quad K = \frac{1}{NT} \sum_i \sum_t K_{it}, \quad \text{and} \quad L = \frac{1}{NT} \sum_i \sum_t L_{it},$$

which allows us to calculate the implied aggregate TFP:

$$TFP = \frac{Y}{(L)^{\alpha \eta} (K)^{(1 - \alpha) \eta}}.$$

To infer the level of aggregate TFP that would prevail in the case of the efficient allocation of

resources, we first need to compute the firm-specific level of TFP using the relationship

$$A_{it} = \frac{Y_{it}}{w_{it}},$$

where $w_{it} = (w_{it}^l)^{\alpha\eta}(w_{it}^k)^{(1-\alpha)\eta}$ is the geometrically-weighted average of the labor and capital wedges. The efficient level of inputs (K_{it}^E, L_{it}^E) , along with the efficient level of output Y_{it}^E , can be obtained using the relationships:

$$K_{it}^E = c_1 A_{it} \bar{w}^k, \quad L_{it}^E = c_2 A_{it} \bar{w}^l, \quad \text{and} \quad Y_{it}^E = A_{it} / \bar{w},$$

where \bar{w}^k and \bar{w}^l are the average capital and labor wedges observed in the data and $\bar{w} = (\bar{w}^l)^\alpha (\bar{w}^k)^{1-\alpha}$. Letting

$$Y^E = \frac{1}{NT} \sum_i \sum_t Y_{it}^E, \quad K^E = \frac{1}{NT} \sum_i \sum_t K_{it}^E, \quad \text{and} \quad L^E = \frac{1}{NT} \sum_i \sum_t L_{it}^E$$

denote the aggregate output, capital, and labor that would be obtained under the efficient allocation of resources, the corresponding implied aggregate TFP—the level of TFP that would prevail in the absence of dispersion in borrowing costs—is given by

$$TFP^E = \frac{Y^E}{(L^E)^{\alpha\eta} (K^E)^{(1-\alpha)\eta}},$$

and the relative TFP loss due to resource misallocation by

$$\log \left(\frac{TFP}{TFP^E} \right).$$

Importantly, by using data on firm-specific sales and borrowing costs, we can infer the relative TFP loss due to resource misallocation without relying on the log-normal approximation.

The results of these two exercises are summarized in Table 2. We calculate the implied TFP losses for all 497 firms in our sample as well as for durable- and nondurable-goods producers separately. The entries under the heading “Approximate” are the implied TFP losses (in percent) calculated using only the dispersion in the firm-specific borrowing costs and rely on the log-normal approximation; the entries under the heading “Actual” are the implied TFP losses that employ information on both borrowing costs and sales. Columns labeled \bar{r} , σ_r , and $[r_{P10}, r_{P90}]$ contain the sample mean, the standard deviation, and the P90–P10 range, respectively, of the average firm-specific borrowing costs, while σ_{w_l} and σ_{w_k} denote the estimates of the cross-sectional standard deviation of the log labor and capital wedges used to compute the approximate TFP losses.

The results in Table 2 indicate that the loss in U.S. manufacturing TFP due to resource misallocation arising from financial market frictions is relatively modest. The losses implied by our

Table 2: TFP Losses due to Resource Misallocation
(Manufacturing Firms with Access to the Corporate Bond Market)

Sector	\bar{r}	σ_r	$[r_{P10}, r_{P90}]$	σ_{w_l}	σ_{w_k}	Relative TFP Loss	
						Approximate	Actual
All Manufacturing	2.43	1.16	[0.84, 4.71]	0.43	0.59	1.75 (3.61)	3.44 -
Durable Goods Mfg.	2.62	1.69	[0.92, 4.99]	0.43	0.60	1.77 (3.65)	3.23 -
Nondurable Goods Mfg.	2.24	1.61	[0.73, 4.67]	0.42	0.58	1.69 (3.48)	3.63 -

NOTE: Sample period: 1985:Q1–2010:Q4; No. of firms = 497; Obs. = 16,975. Real interest rates and the implied TFP losses are in percent. The approximate TFP losses use only the information on the dispersion of firm-specific average real interest rates and rely on the second-order log-normal approximation; the approximate TFP losses reported in parentheses are calculated under the assumption that financial market frictions distort only the choice of the capital input (i.e., $\sigma_{w_l} = 0$). The actual TFP losses employ information on the firm-specific real interest rates and the corresponding real sales (see text for details).

approximation method are about 1.75 percent for the manufacturing sector as a whole and for its two main subsectors. As discussed in Section 3.3, it is possible that in the model where financial frictions distort the choice of both the labor and capital input, the loss in TFP due to resource misallocation is less than the TFP loss in a model where financing constraints apply only to capital. To evaluate this possibility, we also computed the approximate losses assuming that $\sigma_{w_l} = 0$, which are reported in parentheses. Note that in all cases, the implied loss in TFP in the absence of financing constraints on labor is about twice as large as the loss computed under the assumption that financial frictions distort the choice of both inputs. Nevertheless, both sets of estimates imply only a moderate loss in manufacturing TFP due to resource misallocation.

The actual TFP losses—that is, losses computed using the information on firm-specific borrowing costs and the corresponding sales—are around 3.5 percent for the manufacturing sector as a whole; as before, the estimated losses are highly comparable across the two subsectors. From an economic perspective, however, both methods imply TFP losses that are sufficiently close in magnitude, which suggests that the log-normal approximation, especially under the assumption that financial market frictions do not distort the firm’s choice of the labor input, may provide a reasonable estimate of the TFP losses in the case where only information on the dispersion of borrowing costs across firms is available.

With these results in hand, we now consider the implications of two counterfactual scenarios, both of which assume greater dispersion in borrowing costs than actually observed in the U.S. manufacturing data. In the first scenario, we assume that

$$r_{it} = r_t^* + 2s_{it},$$

which roughly doubles the dispersion in firm-level real interest rates; the second scenario counter-

Table 3: Counterfactual TFP Losses due to Resource Misallocation

Scenario	\bar{r}	σ_r	$[r_{P10}, r_{P90}]$	σ_{w_l}	σ_{w_k}	Loss
S1: $r_{it} = r_t^* + 2s_{it}$	4.84	3.30	[1.68, 9.41]	0.68	0.93	4.31 (8.84)
S2: $r_{it} = r_t^* + 10s_{it}$	24.2	16.5	[8.38, 46.7]	1.57	1.95	19.9 (39.3)

NOTE: Real interest rates and the implied TFP losses are in percent. The approximate TFP losses use only the information on the dispersion of firm-specific average real interest rates and rely on the second-order log-normal approximation; the approximate TFP losses reported in parentheses are calculated under the assumption that financial market frictions distort only the choice of the capital input (i.e., $\sigma_{w_l} = 0$).

factually assumes that

$$r_{it} = r_t^* + 10s_{it},$$

which represents a ten-fold increase in the dispersion of borrowing costs.

As reported in the S1 row of Table 3, doubling the dispersion in firm-specific credit spreads implies an approximate loss in manufacturing TFP of 4.3 percent, assuming that financial market frictions distort the firm’s choice of both the capital and labor inputs. Assuming that financing constraints apply only to the capital input, however, implies a TFP loss of almost 9 percent. According to the S2 row, a ten-fold increase in the dispersion of firm-level borrowing costs implies a significant loss in TFP as a result of resource misallocation. Under this counterfactual scenario, the implied loss in TFP, according to our log-normal approximation, is almost 20 percent in the case in which financial frictions distort both the labor market and the market for physical capital. Note, however, that the ten-fold increase in credit spreads that underlies this counterfactual scenario implies an average real interest rate of almost 25 percent, with the P90–P10 range of 8.38 percent to 46.7 percent, extremely high and disperse borrowing costs compared with the actual U.S. data. Indeed, one suspects that they are high even relative to the mean and dispersion in borrowing costs that one is likely to observe in developing economies.

5 Conclusion

This paper developed a simple accounting framework that was used to compute the resource loss due the misallocation of inputs in the presence of financial market frictions. To a second-order approximation, our methodology implies that resource losses may be inferred directly from the dispersion in borrowing costs across firms. Using a direct measure of firm-specific borrowing costs, we show that for a subset of U.S. manufacturing firms, the resource loss due to such misallocation is relatively small—between 1.5 and 3.5 percent of measured TFP. On the whole, our results are consistent with those of Midrigan and Xu [2010], who find that financial market frictions are unlikely to imply large efficiency losses in an economy with relatively efficient capital markets.

Our methodology can easily be used to study the question of what fraction of differences in TFP across countries may be attributable to the misallocation of inputs arising from financial market frictions. Counterfactual experiments indicate that a ten-fold increase in the dispersion in interest rates across firms implies a reduction—through the effect of borrowing costs on resource allocation—in measured TFP of about 20 percent. This finding implies that the dispersion in borrowing costs in developing countries must be an order of magnitude greater than the dispersion of borrowing costs in the United States in order for financial distortions to account for a significant share of the TFP differentials between developed and developing economies.

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