Misallocation losses owing to financial distortions:

Direct evidence from dispersion in borrowing costs.

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Extended Abstract for Submission to the 2011 SED

1 Overview:

Recent research emphasizes the role of resource misallocation as a determinant of cross-country differences in total factor productivity. Following research of Restuccia and Rogerson (2008), estimates by Klenow and Hsieh (2009) imply that such misallocation can account for 50% of the difference between total factor productivity in the China vs the United States for example. Additional research emphasizes the potential role of financial market imperfections in distorting resource reallocation. Buera et al (2009) and Greenwood et al (2010) argue that a large fraction of cross-country TFP differences may be attributed to resource misallocation owing to imperfect capital markets. These results are obtained by choosing model parameters to directly match the size distribution of firms in an environment where financial distortions determine firm size.

More recently, Midrigan and Xu (2010) challenge these findings. In particular, they argue that firms that face severe financial constraints have a strong incentive to save to alleviate the effect of the constraint. According to Midrigan and Xu, in a model that is calibrated to match both the size distribution of firms and the standard deviation of sales growth, there is simply too little variability in observed sales growth to imply important differences in capital costs across firms. According to their estimates, financial distortions account for at most 5% of the TFP difference between Columbia and South Korea (a benchmark country with highly developed capital markets).

Although obtaining strongly different conclusions, the research of Buera et al. (2009), Greenwood et al. (2010) and Midrigan and Xu (2010) all share a common approach in terms of identifying the size of TFP losses owing to resource misallocation using information on the distribution of sales over time and across firms. In this paper, we provide a direct measure of financial distortions based on observed differences in borrowing costs across firms. We develop an accounting methodology to map these observed differences in borrowing costs into measures of aggregate resource misallocation that may plausibly be attributed to financial market imperfections. Using a log-normal approximation we show that this resource misallocation may be inferred from cross-industry or cross-country information on the dispersion in borrowing costs. We also apply our accounting methodology to U.S. Compustat data. Despite fairly large and persistent differences in borrowing costs across firms, our estimates imply relatively modest losses in TFP owing to resource misallocation that is attributable to such differences – roughly on the order of 1% of total TFP for the United

States. We also find that increasing the dispersion in borrowing costs by a factor of 2 only leads to a TFP loss of 3%. To obtain a TFP loss of 17% one must increase the dispersion in borrowing costs by a factor of 10 relative to U.S. data.

Our results can be directly obtained from the log-normal approximation and information on interest rate dispersion 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 these estimated losses 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 Some Preliminary Facts about Borrowing Costs and Firm-Size:

Our empirical analysis focuses on a subset of Compustat firms for which we can observe both sales and corporate credit spreads at the firm-level. This data is obtained by matching Lehman-Warga and Merill-Lynch data on secondary market prices of senior unsecured bonds outstanding with Compustat income and balance sheet data. We use the secondary market prices to infer a credit spread for each bond issuance in our sample. We then compute the firm-specific credit spread as the average credit spread across all outstanding bonds in a given time period. Details of the data set and the methodology used to compute credit spreads are discussed in Gilchrist and Zakrajsek (2009).

Figure 1 plots the distribution of credit spreads for our sample of firms. The mean credit spread is 200 basis points. The standard deviation of credit spreads is 100 basis points. This specific sample truncates credit spreads at the 10% level, thus likely underestimates the true dispersion in credit spreads to a certain extent.

Figure 2 plots the relationship between firm-size and credit spreads for our sample of Compustat firms. Here we plot the average credit spread for each firm over time, along with average firm size. Hence, we may view this relationship as capturing the long-term relationships between firm-size and borrowing costs for U.S. non-financial corporations. The solid line plots the fitted value from regressing the firm-average credit spread on a polynomial function of average firm size. This highlights the strong negative relationship between firm size and borrowing costs observable in U.S. corporate data.

Credit spreads capture both default probabilities and a residual component that relates to firm-specific factors such as recovery in default, and individual pricing components that reflect firm-specific characteristics. Default probabilities are related to leverage of the firm. Thus, to the extent that smaller firms are more leveraged they have higher default probabilities To control for differences in default probabilities across firms we regress credit spreads on expected default frequencies obtained from Moody's KMV estimated default frequency:

$$s_{it} = \alpha_o + \alpha_1 EDF_{it} + \varepsilon_{it}$$

Figure 3 plots the firm-average residual spread ε_i against average firm size. Although the dispersion in spreads is reduced once one controls for expected default we still find a strong negative relationship between residual spreads and firm size. Such permanent differences will imply potentially important effects owing to resource misallocation.

3 Accounting:

In this section of the paper, we discuss our TFP accounting procedure that relates TFP losses owing to resource misallocation to dispersion in 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 in Klenow and Hsieh (2009).

We assume that firms have access to a decreasing returns to scale production function of the form

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

where η measures the degree of decreasing returns. Decreasing returns may be due to managerial span of control as in Lucas (199?) or, alternatively due to monopolistic competition in an environment with Dixit-Stiglizt preferences over heterogenous goods.

We further assume that firms must borrow for both labor and capital inputs at a firm-specific borrowing cost r_i. Let δ denote depreciation and W denote the aggregate wage. The optimal choice of inputs implies that firms equate the marginal revenue products to input costs:

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

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

The optimal capital-labor ratio is:

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

Solving for labor:

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

This implies

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

for some constants c_1 and c_2.

3.1 Labor and capital wedges:

Let

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

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

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

Here w_i^l and w_i^k denote wedges which create 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 $w_i^k = w^k$ across all firms.

3.2 Aggregation and productivity:

Define aggregate labor and capital inputs as:

$$
\begin{aligned}
L &= c_1 \int A_i \omega_i^l di \\
K &= c_2 \int A_i \omega_i^k di
\end{aligned}
$$

Define the wedge in the cost index as:

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

then aggregate output may be expressed as

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

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

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

3.3 A Log-Normal Approximation:

Taking logs we have:

$$\log(TFP) = \log\left(\int A_i \omega_i^{\eta} di\right) - \alpha\eta \log\left(\int A_i \omega_i^{l} di\right) - (1-\alpha)\eta \left(\int A_i \omega_i^{k} di\right)$$

Assume that A_i, w_i^l and w_i^k are jointly log-normality distributed. Let a and σ_a^2 denote the mean and variance of $\log A_i$. Similarly, let ω_k, ω_l and $\sigma_{\omega_l}^2, \sigma_{\omega_k}^2$ denote the mean and variances of $\log(w_i^l)$ and $\log(w_i^k)$ respectively, while covariances are denoted with notation $\sigma_{x,y}$. Then

$$\begin{aligned}\log\left(\int A_i \omega_i^{\eta} di\right) &= a + \eta\left(\alpha\omega_l + (1-\alpha)\omega_k\right) + \frac{1}{2}\sigma_a^2 + \frac{\eta^2\alpha^2}{2}\sigma_{\omega_l}^2 + \frac{\eta^2(1-\alpha)^2}{2}\sigma_{\omega_k}^2 \\ &\quad + \eta\alpha(1-\alpha)\sigma_{\omega_l\omega_k} + \eta\left(\alpha\sigma_{\omega_l,a} + (1-\alpha)\sigma_{\omega_k,a}\right)\end{aligned}$$

$$\log\left(\int A_i \omega_i^{l} di\right) = a + \omega_l + \frac{1}{2}\sigma_a^2 + \frac{1}{2}\sigma_{\omega_l}^2 + \sigma_{\omega_l,a}$$

$$\log\left(\int A_i \omega_i^{k} di\right) = a + \omega_k + \frac{1}{2}\sigma_a^2 + \frac{1}{2}\sigma_{\omega_k}^2 + \sigma_{\omega_k,a}$$

Combining these expressions, implies

$$\log(TFP) = (1-\eta)\left(a + \frac{1}{2}\sigma_a^2\right) + \frac{\eta\alpha(1-\eta\alpha)}{2}\sigma_{\omega_l}^2 + \frac{\eta(1-\alpha)\left(1-\eta(1-\alpha)\right)}{2}\sigma_{\omega_l}^2 - \eta^2\alpha(1-\alpha)corr(\omega_l,\omega_k)\sigma_{\omega_l}\sigma_{\omega_k}$$

In an economy with an efficient allocation of resources, ω_i^k and ω_i^l are constant. Under such circumstances,

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

Hence the resource loss due to misallocation is:

$$\log(TFP/TFP_E) = \frac{\eta\alpha(1-\eta\alpha)\sigma_{\omega_l}^2}{2} + \frac{\eta(1-\alpha)\left(1-\eta(1-\alpha)\right)\sigma_{\omega_k}^2}{2} - \eta^2\alpha(1-\alpha)corr(\omega_l,\omega_k)\sigma_{\omega_l}\sigma_{\omega_k} \quad (1)$$

Several comments are worth making here. First, the resource loss due to misallocation is an increasing function of the dispersion in the labor and capital wedges σ_{ω_l} and σ_{ω_k}.

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 resource loss due to misallocation. Thus, up to a second-order approximation, size-based distortions matter only to the extent that they create dispersion in labor and capital wedges, and not because they are size-based perse.

Third, holding dispersion in labor and capital wedges fixed, a high correlation between labor and capital wedges reduces the overall loss due to resource misallocation.

3.4 Misallocation Loss and Dispersion in Interest Rates:

To derive an approximate relationship between TFP loss owing to misallocation and dispersion in interest rates, note that under the assumption that both labor and capital are fully distorted by financing constraints (i.e. input costs are $r_i+\delta$ for capital and $(1+r_i)w$ for labor, then $corr(\omega_l, \omega_k) = 1$. The log-labor and capital wedges are

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

We can approximate these wedges around $\log(r_i)$:

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

Thus the ratio of the standard deviation of the labor wedge relative to the capita wedge is:

$$
\frac{\sigma_{\omega_l}}{\sigma_{\omega_k}} \approx \frac{\left[(1-(1-\alpha)\eta)(r^2+r\delta) + (1-\alpha)\eta(r+r^2)\right]}{\left[\alpha\eta(r^2+r\delta) + (1-\alpha\eta)(r+r^2)\right]}
$$

The terms involving r^2 and $r\delta$ are an order of magnitude small than the terms involving r. Hence, a rough approximation implies

$$
\frac{\sigma_{\omega_l}}{\sigma_{\omega_k}} \approx \frac{(1-\alpha)\eta}{1-\alpha\eta}.
$$

Using this expression, we can approximate the misallocation loss as a function of $\sigma^2_{\omega_k}$:

$$
\log(TFP/TFP_E) = \left[\frac{\eta(1-\alpha)(1-\eta(1-\alpha))}{2} + \frac{\eta\alpha(1-\alpha\eta)}{2}\left(\frac{(1-\alpha)\eta}{1-\alpha\eta}\right)^2 - \eta^2\alpha(1-\alpha)\frac{(1-\alpha)\eta}{1-\alpha\eta}\right]\sigma^2_{\omega_k} \tag{2}
$$

where

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

The first term in 2 reflects the direct effect of variation in ω_k on the misallocation loss. The second term reflects the direct effect of variation in ω_l on the misallocation loss while the third term is due to the covariance between ω_l and ω_k. Combining these last two terms in equation 2 implies that their net effect is negative:

$$
\log(TFP/TFP_E) = \left[\frac{\eta(1-\alpha)(1-\eta(1-\alpha))}{2} - \frac{\eta\alpha(1-\alpha\eta)}{2}\frac{\sigma^2_{\omega_l}}{\sigma^2_{\omega_k}}\right]\sigma^2_{\omega_k} \tag{3}
$$

It is useful to contrast this result with the case where financial constraints apply only to the capital input choice rather than both capital and labor. In this case there is no distortion in labor inputs owing to financial frictions and $\sigma_{\omega_l} = 0$. The misallocation loss is

$$\log(TFP/TFP_E) = \frac{\eta(1-\alpha)\,(1-\eta(1-\alpha))}{2}\sigma^2_{\omega_k} \tag{4}$$

where the standard deviation of ω_k now satisfies:

$$\sigma_{\omega_k} = \frac{(1-\alpha\eta)}{1-\eta}\frac{r}{r+\delta}\sigma_{\log(r)}$$

Holding σ_{ω_k} fixed, the misallocation loss in the case without labor distortions is strictly greater than the misallocation loss with labor market distortions that are perfectly correlated with the capital distortion. The labor market distortion increases the variability of σ_{ω_k} by the amount $\left(\frac{\alpha\eta}{1-\eta}\right)\left(\frac{r}{1+r}\right)\sigma_{\log(r)}$however. But, because $r/(1+r)$ is a small number, the effect on the variability of σ_{ω_k} is somewhat small. Hence it is still likely to be true that misallocation is greater in the event that only the capital market is distorted even after taking into account the effect of omitting the labor market distortions on σ_{ω_k}.

In the event that financial frictions have no impact on labor hiring, the equation 4 provides a useful approximation to the reallocation loss. In addition, it likely provides an upper bound in the event that financial frictions directly distort the labor market.

4 Preliminary Results:

In this section, we provide some preliminary results on the implied loss due to resource misallocation for the subset of Compustat firms for which we have matched firm-specific corporate credit spreads. To compute the misallocation loss we first rely on the log-normal approximation outlined above. Specifically, we assume that firm-specific borrowing costs r_{it} are equal to the firm-specific credit spread s_{it} plus the average rate of interest r :

$$r_{it} = s_{it} + r$$

We assume that the depreciation rate $\delta = 0.06$ and using this estimate directly compute ω^k_{it} and ω^l_{it}, the log-wedges for capital and labor. Given these wedges, we compute the standard deviations σ_{ω_k} and σ_{ω_l}. We assume that the labor share $\alpha = 2/3$ and that the degree of decreasing returns to scale $\eta = 0.85$. This allows us to compute the log-loss according to equation 1.

This procedure only relies on dispersion in interest rates to compute TFP losses owing to resource misallocation. Given data on firm sales Y_{it} and the wedges w^k_{it}, w^l_{it} it is possible to directly infer the implied inputs K_{it} and L_{it}

using

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

Summing over the implied inputs gives

$$Y = \frac{1}{N}\sum_i \left(\frac{\sum_t Y_{it}}{T}\right)$$
$$K = \frac{1}{N}\sum_i \left(\frac{\sum_t K_{it}}{T}\right)$$
$$L = \frac{1}{N}\sum_i \left(\frac{\sum_t L_{it}}{T}\right)$$

and a measure of aggregate TFP

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

To infer the aggregate level of TFP that would obtain with the efficient allocation of resources we first need to infer the firm-specific TFP, A_{it} from

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

where $w_{it} = \left(w^l_{it}\right)^{\alpha}\left(w^k_{it}\right)^{1-\alpha}$ is the geometric weighted average of the labor and capital wedges. The efficient level of inputs (K^E_{it}, L^E_{it}) along with the efficient level of output Y^E_{it} using the relationships:

$$K^E_{it} = c_1 A_{it} w^k$$
$$L^E_{it} = c_2 A_{it} w^l$$
$$Y^E_{it} = A_{it}/w$$

where w^k and w^l are the mean wedges observed in the data. Let

$$Y^E = \frac{1}{N}\sum_i \left(\frac{\sum_t Y_{it}}{T}\right)$$
$$K^E = \frac{1}{N}\sum_i \left(\frac{\sum_t K_{it}}{T}\right)$$
$$L^E = \frac{1}{N}\sum_i \left(\frac{\sum_t L_{it}}{T}\right)$$

denote the aggregate output, labor and capital that would be obtained under the efficient allocation. The aggregate TFP that would be obtained in the absence of dispersion in borrowing costs is

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

and the resource loss due to misallocation is

$$\log(TFP/TFP^E)$$

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

Figure 4 provides some preliminary estimates of the resource loss $\frac{TFP}{TFP^E}$ broken down by 2 digit industry using the actual data on both sales and borrowing costs. The resource losses are modest, on the order of 1% or less for most industries.

We now consider a comparison of the loss computed under the log-normal approximation with the actual loss computed using the combined information on sales and borrowing costs. We confine our attention to an example that ignores industry differences by simply computing results for the entire sample of Compustat firms for which we available data on both sales and borrowing costs. We begin by computing the loss under the actual distribution. We then consider the implications of two counterfactual exercises which assume greater dispersion in borrowing costs than are actually observed in the U.S. data. The results of these exercises are reported in the table below (referred to as Table 1).

	σ_l	σ_k	$[r_{0.25}, r_{0.75}]$	$LogNormal\ Loss$ (σ_l= 0)	$Actual\ Loss$
$r = 0.045, \sigma_r = 0.016$	0.33	0.45	$[0.034, 0.051]$	0.011 (0.021)	0.006
$r = 0.065, \sigma_r = 0.046$	0.56	0.75	$[0.044, 0.073]$	0.028 (0.058)	0.018
$r = 0.204, \sigma_r = 0.162$	1.50	1.86	$[0.101, 0.245]$	0.181 (0.355)	0.170

The first row of Table 1 provides a comparison of the resource loss computed using the log-normal approximation along with the actual loss inferred from the procedure that uses both sales and borrowing cost data. Column 1 reports the mean and standard deviation of the borrowing cost r_{it}. Column 2 and 3 report the standard deviation of the log-wedges ω^l_{it} and ω^k_{it} necessary to compute the log-approximation. Column 4 reports the inter-quartile range of actual borrowing costs. Column 5 reports the estimated loss under the log-normal assumption. Column 6 computes the actual loss.

Consistent with the industry results reported in figure 4 above, the actual loss is very modest – approximately 0.6 percenage points. The loss implied by the log-normal approximation is slightly higher at 1.1 percentage points. Nonetheless, these numbers are sufficiently similar to suggest that the log-normal provides a reasonable approximation.

The next two rows of table 1 report results for two counterfactual experiments which increase the dispersion in borrowing costs. In the first counterfactual, we set

$$r_{it} = 2s_{it} + r$$

which roughly doubles the dispersion in borrowing costs. Row 3 reports results when we counterfactually assume that

$$r_{it} = 10s_{it} + r$$

which is a ten-fold increase in dispersion.

As reported in the second row of Table 1, doubling the dispersion in spreads now implies a resource loss of 2.8 percentage points under the log-normal approximation and 1.8 percentage points when computing the actual loss using the combined sales and interest rate data.

According to the third row of Table 1, a ten fold increase in dispersion implies significant resource losses owing to misallocation. The estimated loss using the log-normal distributional assumption is 18 percentage points while the actual loss computed using the combined data on sales and borrowing costs is 17.1 percentage points. These numbers are remarkably close and highlight the robustness of the log-normal approximation.

The ten fold increase in spreads used to compute this counterfactual implies a mean borrowing cost of 20 percent. The interquartile range of borrowing costs is [10%, 24%] while the 90% percentile is [2%,64%]. These are extremely high and disperse spreads vis-a-vis U.S. data. 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.

As discussed in the accounting section, it is possible that the resource loss owing to missallocation in the model with borrowing costs for both labor and capital is less than the resource loss that would occur in a model where borrowing costs only apply to capital inputs. To evaluate this possibility, we compute the log-normal loss in the even that $\sigma_{\omega_l} = 0$ as outlined above. These numbers are reported in parenthesis in column four of Table 1. In all cases, the resource loss in the absence of borrowing costs for labor exceeds the resource losses computed with labor borrowing costs. Indeed in the counterfactual cases, the difference is quite large. The counter-factual ten-fold increase in dispersion in interest rates now implies a resource loss on the order of 35 percentage points which is comparable to estimates provided elsewhere in the finance and development literature.

5 Extensions:

In lieu of using borrowing costs, it is possible to infer TFP losses from estimates of the dispersion in the marginal product of capital since given data on MPK_{it}

we can infer r_{it} from the first-order condition:

$$MPK_{it} = r_{it} + \delta$$

MPK_{it} can be directly measured by the profit to capital ratio for Compustat firms, alternatively one can assume a Cobb-Douglas production function and compute the marginal product of capital using the sales to capital ratio. This is a standard approach in the literature. Whether such an approach provides meaningful estimates of borrowing costs is an open question however. In particular, as discussed in Gilchrist and Zakrajsek (2008) much of the dispersion in estimated marginal products of capital reflects industry-specific heterogeneity in markups and depreciation rates. After controlling for such industry-wide differences, we can make a direct comparison between these two approaches, one that relies on estimates obtained from dispersion in profit rates or sales to capital ratios and the other than relies on estimates obtained directly from the observed cost of borrowing.

Our accounting procedure that relies on direct estimates of borrowing costs raises further methodological issues. First, is it possible to infer borrowing costs in the absence of interest rate data? Recent work by Gilchrist and Zakrajsek suggests that one can obtain rough estimates directly from accounting data on leverage, volatility of assets and other measures that may be combined and calibrated in such a way as to match information on credit spreads for a subsample of firms. Such a procedure would allow us to potentiall compute an implied borrowing costs for nearly all publicly traded firms reported in Compustat. This procedure is easily generalizable to publicly traded firms in other countries. Second, are there estimates of borrowing costs for non-publicly trade firms? For the U.S. the answer is yes at least for firms large enough to access the syndicated loan market. Dealscan provides a rich data set with information on borrowing costs at issuance for all syndicated loans in the United States. Finally, the Senior Loan Officer Survey of the Board of Governors provides information on lending rates to commercial firms in the United States. This data is also readily available and easy to integrate into the analysis.

Given the robustness of our log-normal approximation, we expect to use the procedure outlined above to calculate losses owing to resource misallocation for developing economies for which we can obtain data on borrowing costs. We are currently in the process of obtaining firm-specific borrowing costs for Chilean firms from a proprietary data set put together by the Central Bank of Chile. This data also provides information on firm size which allows us to again directly compare results of the log-normal approximation with the actual loss computations as outlined above.

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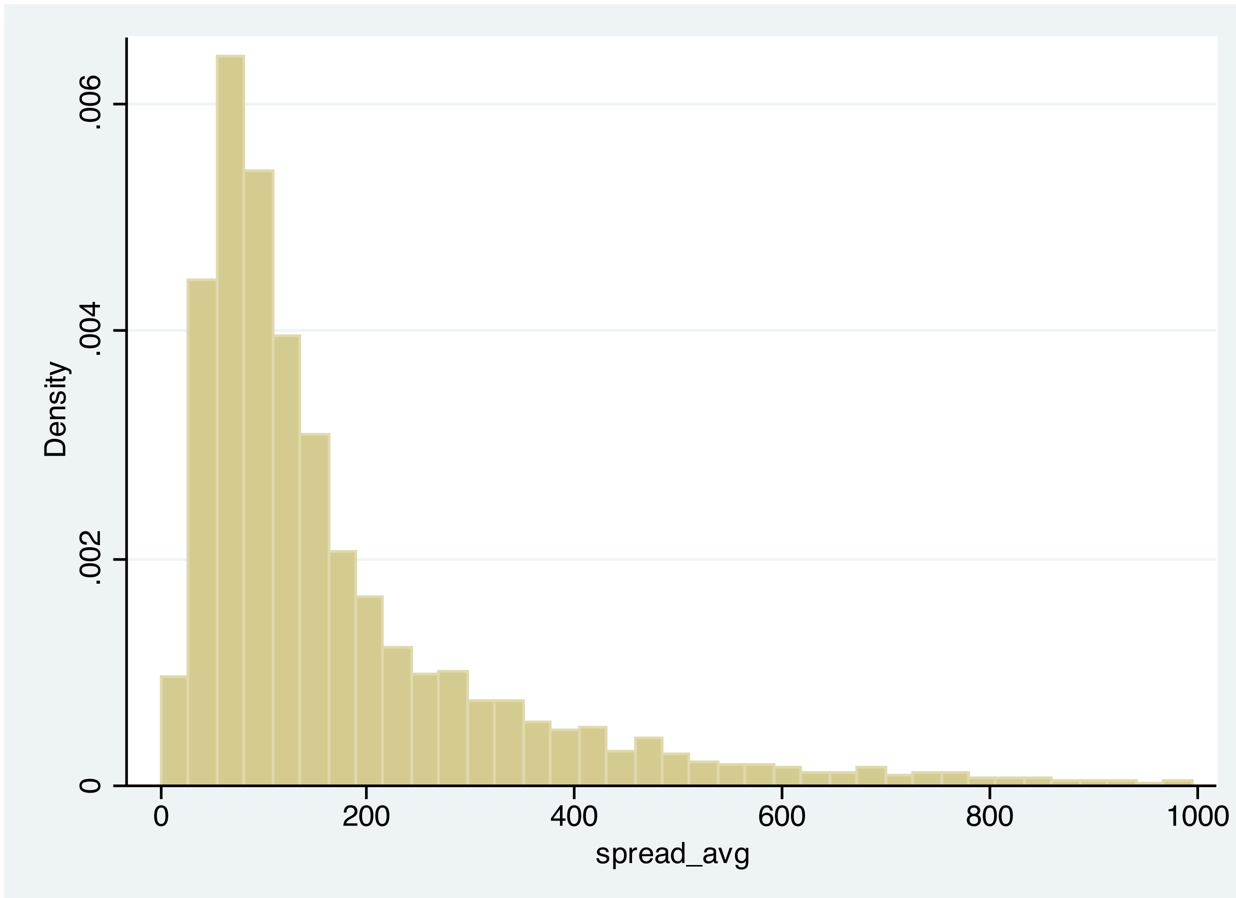

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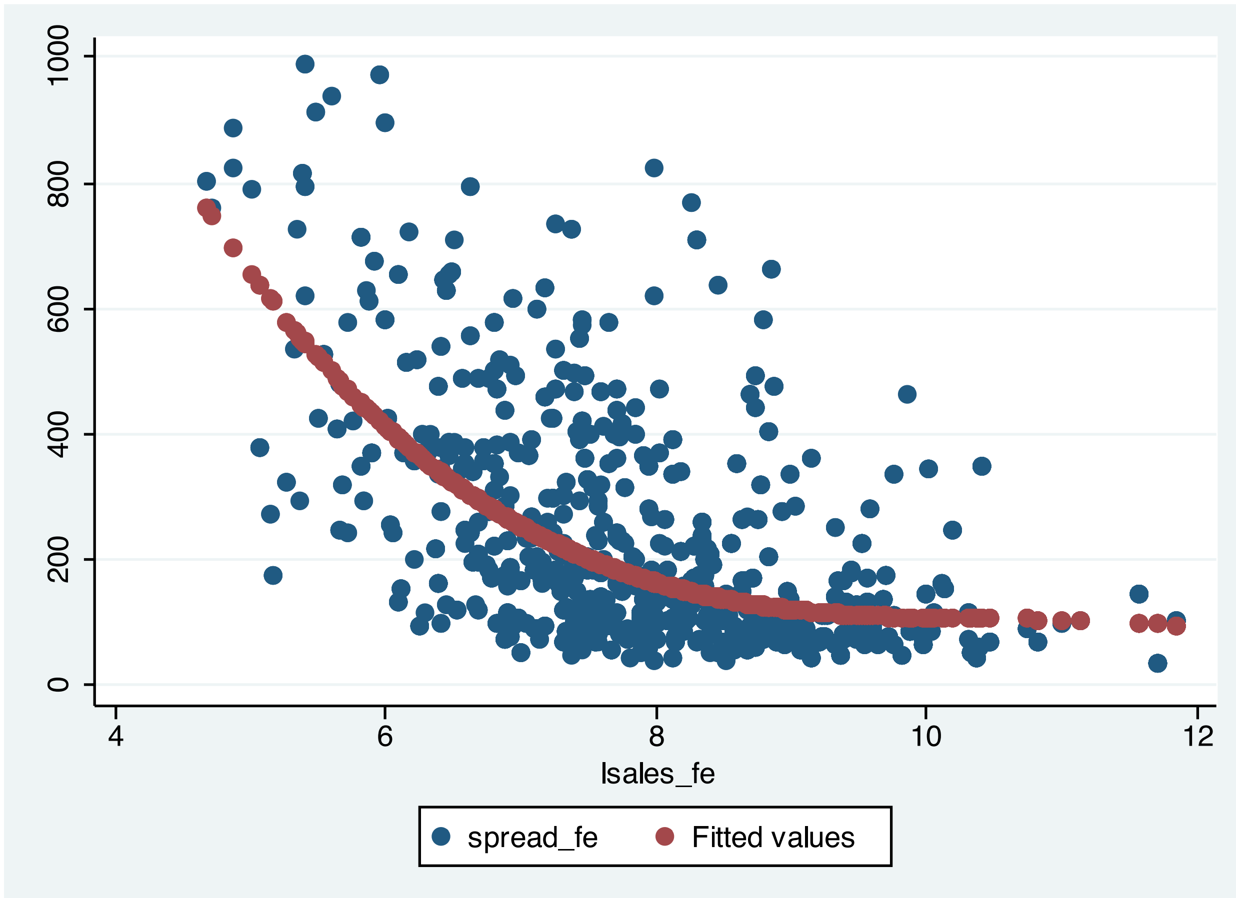

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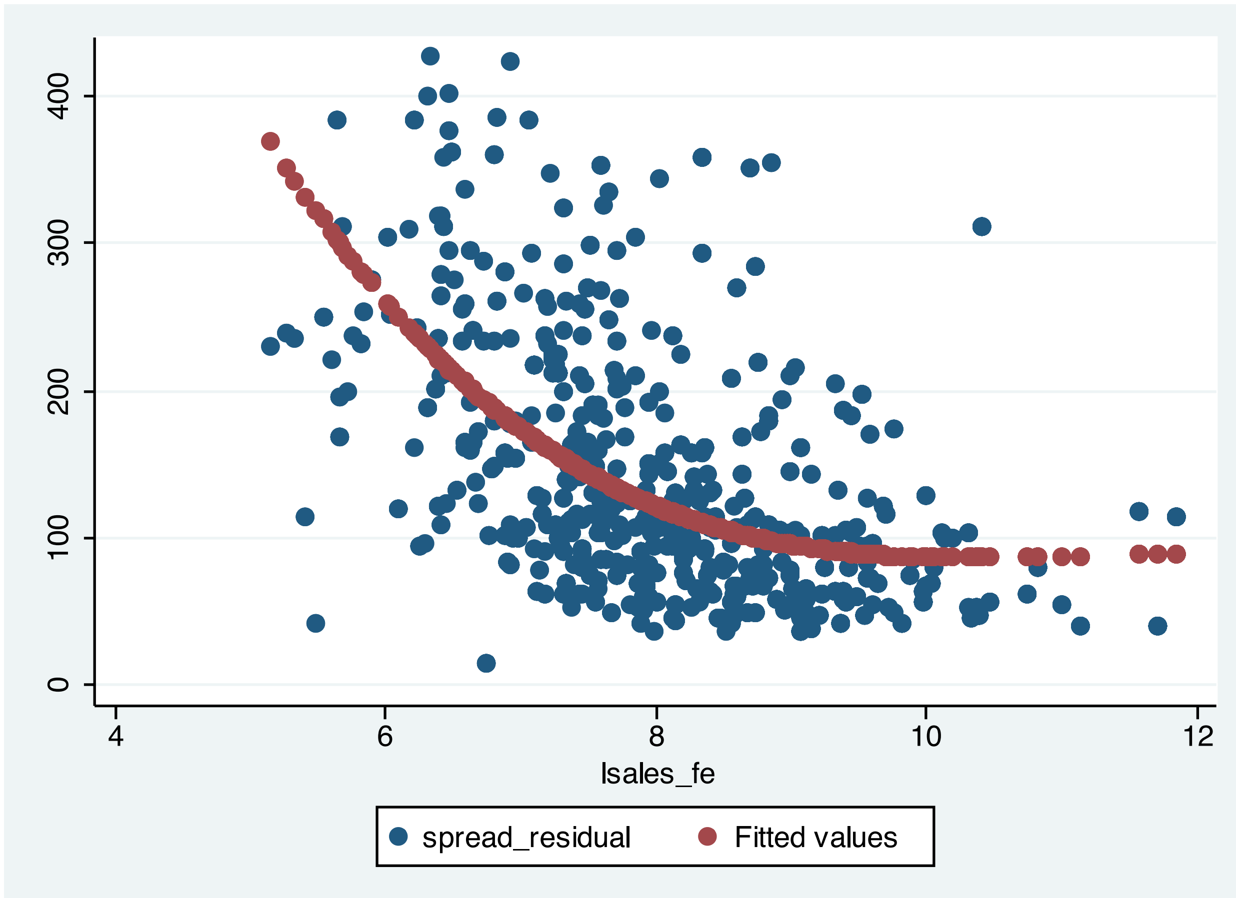
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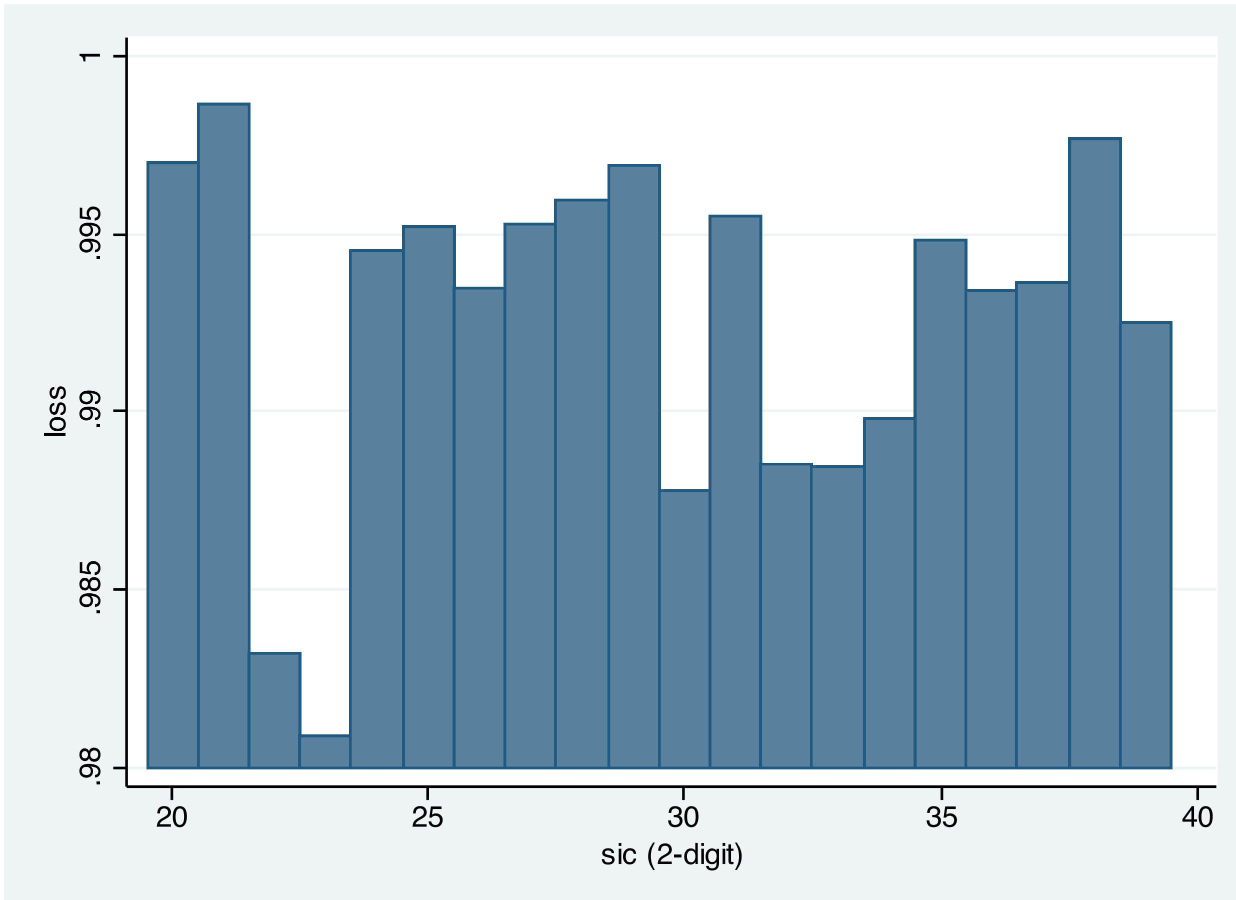
spread_residual
Fitted values


loss
1
.995
.99
.985
.98
20
25
30
35
40
sic (2-digit)