Size-Dependent Intermediate Input Distortions and Misallocation

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Abstract

This paper shows that, by mis-specifying firms as value-added producers, the standard approach ignores intermediate input distortions and therefore substantially underestimates the true extent of misallocation. In the Chinese firm-level data, this value-added approach misses 35% of potential gains from reallocation. Estimates of value-added productivities are downward-biased due to intermediate input distortions, with most productive firms being most affected since distortions in the data are size-dependent. We provide evidence that intermediate inputs are subject to pay-in-advance and financial frictions and we incorporate these frictions into an industry dynamics model. In the calibrated model, the value-added approach underestimates the misallocation by 24% due to size-dependent financial frictions on intermediate inputs. These frictions account for 17% of the total misallocation in the Chinese economy.

JEL Codes: E44, G31, G32, L60, O33, O47

Key Words: Misallocation, Intermediate Inputs, Size-Dependent Distortions, Financial Frictions

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A large body of misallocation literature models firms as value-added producers with capital and labor as inputs and value-added as output, including the seminal paper of Hsieh and Klenow (2009). This approach implicitly assumes that firm-level intermediate inputs and value-added are perfect substitutes. As a result, any distortions on the former do not affect how economists empirically quantify misallocation in value-added units. This assumption is, however, at odds with input-output studies (e.g., Jones, 2011; Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012) that use micro-founded gross-output measure and are crucially built on the complementarity between intermediate inputs and primary inputs of capital and labor.

Given this complementarity, a natural question is how intermediate input distortions affect the measured misallocation under the Hsieh and Klenow (2009)'s approach (the HK approach, henceforth).[1] Presumably, distortions alter the choice of firm-level intermediate inputs and consequently become part of value-added productivities. Reallocation of inputs according to this distorted productivity measure may give a different estimate of misallocation from the true one, especially when more productive firms are distorted more.[2] This paper aims to provide an empirical and quantitative evaluation on the direction and magnitude of this difference in the measured misallocation. We highlight the important role of size-dependent financial frictions on intermediate inputs in contributing to the difference.

To define the *true* measure of misallocation, we refer to *the gross-output approach* (the GO approach, henceforth) that quantifies potential value-added gains from reallocating capital, labor, and intermediate inputs by *modeling firms as gross-output producers*.[3] This approach eliminates the dispersion of marginal products of intermediate inputs across firms, while the HK approach does not.

The first part of the paper shows theoretically that the GO specification does not yield the HK estimate as a reduced-form result and that the HK estimate is thus biased, whenever intermediate input distortions differ across firms. Under assumptions of Cobb-Douglas production functions and a CES industry-level aggregation, larger intermediate input distortions (in absolute value) induce a lower HK estimate of

[1] See the example of legal enforcement frictions on intermediate input deliveries in Boehm and Oberfield (2018).

[2] The importance of such size-dependent distortions was highlighted by Restuccia and Rogerson (2008) and Guner, Ventura, and Xu (2008).

[3] We use phrases of *potential gains* and *actual losses* interchangeably, despite the fact that they have their numerator and denominator flipped in one compared to the other. Both phrases are viewed as *the measured misallocation*. Further, the word *productivity* means *gross-output productivity* unless otherwise notified.

value-added productivity. For sufficiently productive firms, the downward bias from distortions worsens if intermediate input distortions are more size-dependent as in Restuccia and Rogerson (2008) and Guner et al. (2008). As a result, top productive firms receive fewer inputs from reallocation than they do under the GO approach, leading to a potential downward bias on the measured misallocation. We confirm this theoretical result in the Chinese Annual Survey of Industrial Firms (ASIF) data (1998-2007). For an average 2-digit Chinese Industry Classification (CIC) code industry, the input reallocation based on the HK approach would result in 103% gain in value added, while the one based on the GO approach yields 159% gain.

Our analysis also holds if we change the name of size-dependent intermediate input distortions into size-dependent output market distortions, as they result in the same wedge in firms' first-order conditions. To validate our focus on the former, the second part of the paper provides evidence of two specific intermediate input frictions: pay-in-advance and financial frictions. The pay-in-advance is proxied by the industry-level days on inventory (DI) from earlier U.S. studies of Ramey (1989) and Raddatz (2003). In the Chinese data, industries with a longer pay-in-advance exhibit a higher dispersion of log marginal revenue products of intermediate inputs ($logMRPM$), suggesting a larger misallocation for these industries.

Due to this timing requirement, firms need working capital to finance intermediate input purchases. We document two pieces of evidence on how firms could thus be financially constrained. First, the level of $logMRPM$ decreases in age and asset within industries, suggesting younger and smaller firms face larger distortions with fewer intermediate inputs and higher returns.

Second, using data across Chinese provinces, we find that a greater financial development, proxied by the NERI indices,[4] is associated with a smaller within-industry dispersion of $logMRPM$. In the Chinese data, one standard deviation increase in the financial market development decreases the within-industry dispersion of $logMRPM$ by 8%. This empirical relation is especially pronounced among financially vulnerable industries (i.e., a low asset tangibility and a high external finance dependence as in Rajan and Zingales (1998) and Braun (2003)) with a long pay-in-advance. For an industry with the asset tangibility one standard deviation below the aver-

[4]The NERI indices are published by the National Economic Research Institute. We use two indices both on a 0 to 10 scale: one reflecting the fraction of loans lent to non-state owned firms and the other the share of deposits held by non-state owned banks. While the former is the preferred measure, we verify the robustness of our results using the latter as the measure of financial development.

age, the financial market development is associated with an additional decrease of 3 percentage points in the dispersion of $logMRPM$. Meanwhile, if the industry has a longer pay-in-advance than the average, there would be another further decrease of 7 percentage points. Results are quantitatively similar if we use the alternative vulnerability measure of external finance dependence.

Are the two intermediate input frictions a candidate to understand why the HK approach underestimates the measure of misallocation in the Chinese data? How do the frictions quantitatively compare to capital frictions in the literature (e.g., Bartlesman, Haltiwanger, and Scarpetta, 2013; Asker, Collard-Wexler, and De Loecker, 2014; Midrigan and Xu, 2014) in shaping misallocation? To answer these questions, we need a model that can endogenously generate the dispersion of marginal revenue products (i.e., distortions) as we observe in the data. The model is of a representative industry à la Hopenhayn (1992), absent input-output linkages. We specify the financial friction as costly equity and debt issuances (e.g., Cooley and Quadrini, 2001; Arellano, Bai, and Zhang, 2012). Firms maximize net present values of future dividends given stochastic productivities and an option to default their debt every period. Firms also decide and pay a fraction of intermediate inputs a period ahead, by which firms need to finance intermediate input purchases in addition to capital investment and its adjustment costs. Competitive intermediaries lend and charge an interest rate that reflects the default risk. The stationary firm size distribution is obtained by having new entrants and exits every period.

We calibrate the model to match key moments of productivity, leverage, the relative size of entrants, the speed of firm growth, and the concentration of sales of large producers in the Chinese ASIF data. We simulate a firm-level dataset as the ASIF analog. In this simulated data, the potential value-added gain under the HK approach is 24% smaller than under the GO approach, consistent with our empirical findings above.[5] This result is driven by size-dependent financial frictions on intermediate inputs in the model and the model well replicates the positive correlation between distortions and productivities in the Chinese data. Using the correct GO approach, the model accounts for about 71% of the potential gross-output gain and 43% of the value-added gain in the Chinese ASIF data.[6]

[5]The gains from reallocation in the simulated data are 45% under the HK approach and 69% under the GO approach. One key reason why the misallocation numbers are smaller in the simulated data is the absence of subsidies (negative wedges) in the model, which are present in the empirical analysis above.

[6]The difference between the two percentages arises from the heterogeneous intermediate input

We then answer the question how quantitatively important intermediate input distortions are in shaping misallocation in the benchmark model and in the Chinese economy. Counterfactual experiments decompose the total misallocation by removing subsets of frictions. Results show that intermediate input frictions, primarily the financial friction, account for 24% and 17% of the potential gross-output gains in the benchmark model and in the Chinese economy, respectively. These numbers are one third as large as the magnitude of misallocation induced by the time-to-build friction on capital. Therefore, although the model has a rich specification of frictions, we find the dynamic nature of capital with stochastic firm-level productivities contributing most of the misallocation, consistent with Asker et al. (2014). Furthermore, the combined gross-output loss from adjustment costs and financial frictions on capital, primarily the former, is 10% and 7% of the misallocation in the benchmark model and in the Chinese economy, respectively. The comparison between output losses generated by capital and intermediate input frictions implies a greater importance of financial market development in allocating inputs than previously discussed in the capital misallocation literature.

This paper builds on several strands of the literature. First, it is related to an earlier literature on size-dependent distortions and misallocation. Restuccia and Rogerson (2008) and Guner et al. (2008) show that distortions in the form of a higher tax on more productive firms induce a larger decline in the aggregate productivity, compared to uncorrelated distortions. In contrast, in Hsieh and Klenow (2009), Asker et al. (2014), Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017) and many others, the magnitude of misallocation is simplified to a dispersion statistic of wedges and the correlation between productivities and distortions plays no role. Baqaee and Farhi (2020) reconcile the two strands and show that the Hsieh and Klenow (2009)'s simplification holds only if distortions and productivities are log normally distributed and otherwise, their correlation matters. This paper argues the importance of size-dependent intermediate input distortions in driving the divergence between the HK and GO approaches for measuring misallocation. With respect to studying this divergence, Hang, Krishna, and Tang (2020) is closest to our paper yet they keep the log normality assumption. Our departure from this assumption is supported by the statistical rejection of the log-normality in the Chinese data.

Second, this paper is related to a growing literature that studies intermediate inputs and misallocation. Most discussion focuses on the input-output transmission

revenue shares across industries in the ASIF data that is absent in the model.

of sectoral distortions to the aggregate economy (e.g., Jones, 2011; Acemoglu et al., 2012; Liu, 2019; Baqaee and Farhi, 2020; Osotimehin and Popov, 2020; Hang et al., 2020). These studies assume a reduced-form wedge on intermediate inputs. In a similar spirit to Boehm and Oberfield (2018), we contribute to the literature in naming two novel intermediate input frictions behind the wedge.

Third, we are related to the literature on financially constrained capital and misallocation. One view states that the misallocation caused by this channel could be moderate since firms can self-finance. Self-financing does not undo misallocation when productivities are less persistent (Caselli and Gennaioli, 2013), when there are fixed cost barriers (Midrigan and Xu, 2014) , when the initial state of the economy is badly misallocated (Buera and Shin, 2013), and when borrowing constraints are endogenous and tighter for smaller and younger firms (Gopinath et al., 2017; Bai, Lu, and Tian, 2018). This paper quantitatively shows that financial frictions would have a larger impact on misallocation if it constrains both capital and intermediate inputs.

Lastly but not leastly, we are related to the literature of misallocation in China. Hsieh and Klenow (2009) first find substantial misallocation in the Chinese data. Brandt, Van Biesebroeck, and Zhang (2012) further document a limited input reallocation across firms in China despite its high TFP growth. Explanations for misallocation include preferred lendings to the state-owned firms (Song, Storesletten, and Zilibotti, 2011; Brandt, Tombe, and Zhu, 2013), trade and migration costs (Tombe and Zhu, 2019), entry costs (Brandt, Kambourov, and Storesletten, 2018), and financial frictions (Bai et al., 2018), to name a few examples. Similar to some of these studies, we base our analysis on the Chinese data with a general message applicable to other economies.

The rest of this paper is structured as follows. Section 1 illustrates the inequivalence between the HK and the GO approaches. Section 2 provides direct evidence on two intermediate input frictions. Section 3 introduces the model. Section 4 calibrates the model, computes the misallocation in the model, implements decomposition exercises, and discusses economic mechanisms. Section 5 concludes.

1 The In-equivalence

This section assumes that the real-world firm-level data is generated by a true model where firms produce gross output. We show the in-equivalence between the HK and the GO approaches for measuring the misallocation when intermediate input distortions exist. Using the Chinese firm-level data, we show size-dependent intermediate input distortions as the main reason why the HK approach may underestimate the measured misallocation.

1.1 Conceptual Framework

Suppose the true model is as follows. Firm i in industry s with productivity A_{is} produce gross output Y_{is} according to the following function:

$$Y_{is} = A_{is} M_{is}^{\beta_m^s} (K_{is}^{\beta_k^s} L_{is}^{1-\beta_k^s})^{1-\beta_m^s} \tag{1}$$

where K, L, and M represent capital, labor, and intermediate inputs. $\beta_k^s(1-\beta_m^s)$, $(1-\beta_k^s)(1-\beta_m^s)$, and β_m^s are their industry-specific cost shares, respectively. By monopolistic competitions with an elasticity of substitution σ, the industry-level aggregation is

$$Y_s = (\sum_{i=1}^{N_s} Y_{is}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{2}$$

Firm i faces an intermediate input distortion τ_{is}^m, a capital distortion τ_{is}^k, and a labor distortion τ_{is}^l:

$$MRPX_{is} = (1+\tau_{is}^x)P_x \tag{3}$$

where $x \in \{K, M, L\}$ and P_x is its factor price. Under the GO approach, we reallocate capital, labor, and intermediate inputs to equalize $MRPX$s within industries, i.e., eliminating wedges in equation (3).

The HK approach, however, specifies a value-added production function:

$$Y_{is}^v = A_{is}^v K_{is}^{\alpha_k^s} L_{is}^{\alpha_l^s} \tag{4}$$

where Y_{is}^v is the value-added quantity and A_{is}^v is its productivity. α_k^s and α_l^s are the industry-specific value-added cost shares of capital and labor, respectively. We assume that the value-added revenue is $P_{is}Y_{is} - P_m M_{is}$, i.e., the distortion τ_{is}^M being non-pecuniary. The industry-level aggregator is specified as:

$$Y_s^v = (\sum_{i=1}^{N_s} (Y_{is}^v)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{5}$$

with an industry-level value-added price as P_s^v. The HK reallocation exercise thus equalizes marginal revenue products of capital and labor according to equation (4) and (5) within industries.

How is equation (4) related to the true production function of equation (1)? Applying the first-order condition of intermediate inputs and the properties of monopolistic competitions, we have

$$A_{is}^v(\tau_{is}^m) = \{\frac{(P_s Y_s^{\frac{1}{\sigma}})^{\frac{1}{1-\tilde{\beta}_m^s}}}{P_s^v (Y_s^v)^{\frac{1}{\sigma}}} \chi_{is}(\tau_{is}^m)\}^{\frac{\sigma}{\sigma-1}} A_{is}^{\alpha_a^s} \tag{6}$$

where $\alpha_a^s = \frac{1}{1-\tilde{\beta}_m^s}$. P_s and P_s^v are industry-level gross-output and value-added prices. Cost shares are

$$\alpha_k^s = \frac{\beta_k^s(1-\beta_m^s)}{1-\tilde{\beta}_m^s}; \alpha_l^s = \frac{(1-\beta_k^s)(1-\beta_m^s)}{1-\tilde{\beta}_m^s}; \tilde{\beta}_m^s = \beta_m^s \frac{\sigma-1}{\sigma}; \alpha_k^s + \alpha_l^s < 1 \tag{7}$$

(see proof in the appendix). A decreasing-return-to-scale function is needed for a direct mapping between the HK and the GO approaches, if we use the same σ in equations (2) and (5).[7]

The existence of intermediate input distortions τ_{is}^m distorts $logA_{is}^v(\tau_{is}^m)$ via

$$\chi_{is}(\tau_{is}^m) = [1 - \frac{\tilde{\beta}_m^s}{1+\tau_{is}^m}][\frac{\tilde{\beta}_m^s}{(1+\tau_{is}^m)P_m}]^{\frac{\tilde{\beta}_m^s}{1-\tilde{\beta}_m^s}} \tag{8}$$

that has properties as follows.[8]

Proposition 1. *For $\tau_{is}^m \in [\tilde{\beta}_m - 1, \infty]$, the value-added production function is*

[7] Alternatively, we can set $\alpha_k^s = \beta_k^s$ and $\alpha_l^s = 1 - \beta_k^s$ with a smaller elasticity of substitution $\tilde{\sigma} = (1-\beta_m^s)\sigma + \beta_m^s$ as in Hang et al. (2020). Gains with the alternative parameter levels are similar to what follows.

[8] When τ_{is}^m is pecuniary, we can show that $P_{is}^v Y_{is}^v = P_{is}Y_{is} - (1+\tau_{is})^m P_m M_{is}$ and $\chi_{is}(\tau_{is}^m) = [1-\tilde{\beta}_m^s][\frac{\tilde{\beta}_m^s}{(1+\tau_{is}^m)P}]^{\frac{\tilde{\beta}_m^s}{1-\tilde{\beta}_m}}$, which is decreasing in τ_{is}^m. Hence, the following result of downward-biased value-added productivities for firms with high τ_{is}^m still holds in this scenario.

well-defined with the gross-output value exceeding the intermediate input cost. Let $\Delta log A^{v}(\tau_{is}^{m}) = log(A_{is}^{v}(\tau_{is}^{m})) - log(A_{is}^{v}(0))$*, i.e., the deviation of the actual value-added productivity from the level absent intermediate input distortions. We have*

(1) $\Delta log A^{v}(\tau_{is}^{m}) \leq 0$ *with a maximum 0 at* $\tau_{is}^{m} = 0$*.* $\Delta log A^{v}(\tau_{is}^{m})$ *decreases with* τ_{is}^{m} *for* $\tau_{is}^{m} \geq 0$ *and increases with* τ_{is}^{m} *for* $\tau_{is}^{m} < 0$*.*

(2) Suppose $\tau_{is}^{m} = c_0 + \rho log A_{is} + \zeta_{is}$ *and* $\rho \neq 0$*. The average deviation conditional on the gross-output productivity,* $E(\Delta log A_{is}^{v} | A_{is})$*, decreases in* $log A_{is}$ *for* $log A_{is} \in [-\frac{1+2ac_0}{2a\rho}, \infty)$ *and increases for* $log A_{is} \in (-\infty, -\frac{1+2ac_0}{2a\rho})$*, where* $a = 0.5\frac{\tilde{\beta}_{m}^{s}(1-\tilde{\beta}_{m}^{s})-1}{(1-\tilde{\beta}_{m}^{s})^2} < 0$*.*

(3) The average deviation conditional on the gross-output productivity, $E(\Delta log A_{is}^{v} | A_{is})$*, decreases in* ρ *for sufficiently large* $log A_{is}$*.*

Proof. See proof in the appendix. □

Proposition 1 states that first, the value-added productivity decreases when the intermediate input distortion τ_{is}^{m} increases in its absolute value, i.e., a hump-shaped deviation curve. Intuitively, firms maximize the gap between gross output and intermediate input costs when $\tau_{is}^{m} = 0$. Any deviation from this maximum causes a smaller value-added gap and consequently a lower $log A_{is}^{v}$. Second, the same hump shape is preserved for the average deviation curve along the dimension of true productivities $log A_{is}$ as long as productivities correlate with intermediate input distortions. Third, when true productivities $log A_{is}$ increasingly correlate with distortions τ_{is}^{m} (i.e., size-dependent distortions in Guner et al. (2008) and Restuccia and Rogerson (2008)), the negative deviation of $log A_{is}^{v}$ is more severe on average for firms on the right tail of the $log A_{is}$ distribution. This feature causes a disproportionate downward bias on the value-added productivity for most productive firms.

To see how the biased value-added productivity influences the input reallocation, note that the "efficient" capital $K_{is}^{eff,v}$ and labor $L_{is}^{eff,v}$ under the HK approach are

$$K_{is}^{eff,v} = \frac{(A_{is}^{v})^{(\sigma-1)/\alpha_{a}^{s}}}{\sum_{i=1}^{N_s}(A_{is}^{v})^{(\sigma-1)/\alpha_{a}^{s}}} K_s,\ L_{is}^{eff,v} = \frac{(A_{is}^{v})^{(\sigma-1)/\alpha_{a}^{s}}}{\sum_{i=1}^{N_s}(A_{is}^{v})^{(\sigma-1)/\alpha_{a}^{s}}} L_s \tag{9}$$

as opposed to those under the GO approach

$$K_{is}^{eff} = \frac{(A_{is})^{\sigma-1}}{\sum_{i=1}^{N_s}(A_{is})^{\sigma-1}}K_s,\ L_{is}^{eff} = \frac{(A_{is})^{\sigma-1}}{\sum_{i=1}^{N_s}(A_{is})^{\sigma-1}}L_s \tag{10}$$

Proposition 1 implies that $K_{is}^{eff,v} = K_{is}^{eff}$ and $L_{is}^{eff,v} = L_{is}^{eff}$ only if firms are identically distorted with a constant τ_s^m within industries.

We then measure the potential within-industry value-added gain as in Hsieh and Klenow (2009):

$$log\left(\frac{(\sum_{i=1}^{N_s}(Y_{is}^{v,eff})^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}}{(\sum_{i=1}^{N_s}(Y_{is}^{v,actual})^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}}\right) \tag{11}$$

where $Y_{is}^{v,eff}$ and $Y_{is}^{v,actual}$ are the "efficient" and actual value-added quantities under the HK approach. For the GO approach, we follow Hang et al. (2020) and write the equivalent within-industry value-added gain as

$$\frac{1}{1-\tilde{\beta}_m^s}log\left(\frac{(\sum_{i=1}^{N_s}(Y_{is}^{eff})^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}}{(\sum_{i=1}^{N_s}(Y_{is}^{actual})^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}}\right) \tag{12}$$

derived from a general equilibrium input-output model in their paper.[9] Y_{is}^{eff} and Y_{is}^{actual} are the efficient and actual gross-output quantities. Hang et al. (2020) show that equations (11) and (12) are equivalent absent intermediate input distortions. Under the log normality assumption on productivities and distortions, they further show that the HK approach may overestimate if the variance of τ_{is}^m is large and if the intermediate input distortions positively correlate with the distortions on capital and labor. Vice versa. However, we implement Shaprio-Wilk tests in the Chinese firm-level data and robustly reject the log-normality assumption for the distributions of $logA_{is}$, τ_{is}^m, and τ_{is}^k under the 1% significance level. Therefore, as theoretically proven in Baqaee and Farhi (2020), the correlation between distortions and productivities could matter for the measures of misallocation in equations (11) and (12). Our next

[9]In Hang et al. (2020), intermediate inputs M is a Cobb-Douglas aggregate of gross output from different industries. We simplify our exposition by directly applying their result. In the later quantitative model with one representative industry, we follow this formula by assuming intermediate inputs are the gross output of this representative industry, i.e., one industry input-output structure.

subsection investigates roles played by these different pieces in the Chinese firm-level data.

1.2 The In-equivalence in Data

This subsection calculates value-added gains under both approaches in the Chinese firm-level data. For most industries and years, the HK approach underestimates measured misallocation because of size-dependent intermediate input distortions.

1.2.1 Data Description

The empirical part of the paper uses the Chinese ASIF data collected by the National Bureau of Statistics (NBS) from 1998 to 2007 (see, e.g., Hsieh and Klenow, 2009; Brandt, Van Biesebroeck, and Zhang, 2014; Bai et al., 2018; David and Venkateswaran, 2019). The dataset contains firm-level balance sheet, income, and cash flow statements for all state-owned manufacturing firms and non-state owned ones with sales above 5 million yuan before 2007.[10] Here a firm is a unique ID registered at the State Administration for Industry and Commerce (SAIC).

Variables of interest include gross output, the book value of capital, employment, wage bill, intermediate input cost, opening year, inventory, payable, receivable, interest expense, total liability, ownership, and industries. Industries are defined at the 2-digit CIC level.

1.2.2 Calculating Gains under the Two Approaches

We set the industry-level intermediate revenue share $\tilde{\beta}_m^s$ from the Chinese input-output table in the OECD database.[11] As in Hsieh and Klenow (2009), we choose the capital share $\beta_k^s = 0.5$ for all industries. The elasticity of substitution σ is 6.67 for consistency with the later quantitative analysis and is between 3 to 10 in Broda and Weinstein (2010).

[10] The sales threshold also became applicable for state-owned firms starting in 2007. In 2011, the threshold increased to 20 million yuan.

[11] We use the Chinese share as our benchmark since countries like China, Czech, Slovak, and historically South Korea and Japan have a higher intermediate share than the OECD average of 0.50 (Jones, 2011). It is hard to think that distortions increase the intermediate input share from 0.5 to 0.6. We believe that the global division story drives this pattern and these countries specialize in production technologies with more intermediate inputs.

To compute wedges in equation (3), we use the gross-output sales for $P_{is}Y_{is}$, the wage payment for effective units of labor for L_{is}, the capital stock for K_{is}, and the intermediate input cost for M_{is}, all in constant 1998 yuan.[12] For each year, we then trim the top and bottom 1% of the log TFPR and log TFPQ distributions calculated from equation (1) and (3).[13] We also drop observations with the gross-output value smaller than the intermediate input cost.

For each 2-digit CIC industry every year, potential gains are measured by equations (11) and (12). From 1998 to 2007, an average industry could increase its value-added by 103% and 159% under the HK and the GO approaches, respectively. We take an average of industry-level gains using the actual industry-level value-added revenues as weights for both approaches (Hang et al., 2020). This comparison suggests that the HK approach underestimates the magnitude of misallocation.[14]

Figure 1 illustrates why the HK approach gives a smaller measured misallocation. The left panel of the figure plots averages of $\Delta log(A_{is}^{v})$ across deciles of intermediate input distortions and the right panel plots the averages across deciles of $logA_{is}$ in the pooled 1998 - 2007 data. Consistent with Proposition 1, both plots are hump-shaped: the downward deviation of $log(A_{is}^{v})$ is more pronounced on the tails of the distortion and productivity distributions. For the top 10% productive firms, the downward deviation could be about 35%, suggesting that these firms may receive too little capital and labor under the HK approach according to equation (9). Although firms on the left tail of the productivity distribution also have a downward-biased $logA_{is}^{v}$, they are far smaller to influence the industry-level reallocation gains. As a result, the HK approach delivers a smaller gain compared to the GO approach.

However, the HK approach does not always underestimate. For 13% of industry-year observations, the HK approach gives a larger gain. Figure 2 shows chemical fiber, nonferrous metals, and other manufacturing as examples in 2004, in contrast to most industries such as textiles, petroleum refining, and instruments.

[12] We construct the capital stock using a perpetual inventory method, setting the initial year as 1995. For mor discussions, see Brandt et al. (2012).

[13] $logTFPR_{is} = logP_{is}Y_{is} - \beta_k^s(1-\beta_m^s)logK_{is} - (1-\beta_k^s)(1-\beta_m^s)logL_{is} - \beta_m^s logM_{is}$; $logTFPQ_{is} = logY_{is} - \beta_k^s(1-\beta_m^s)logK_{is} - (1-\beta_k^s)(1-\beta_m^s)logL_{is} - \beta_m^s logM_{is}$.

[14] We test the robustness of this result by changing parameter values and further trimming the τ_{is}^{m} distribution. If we decrease $\tilde{\beta}_m^s$ to an average of 0.53 in the U.S. NBER-CES database, gains are 176% under the HK approach and 193% under the GO approach for an average industry. If we further let $\sigma = 3$ as in Hsieh and Klenow (2009), the gains are 34% and 100%, respectively. Meanwhile, if we trim the top 1% distribution of τ_{is}^{m} across industries, gains are 107% and 123%, respectively.

To rationalize the cross-industry difference, we study how intermediate input distortions τ_{is}^{m} distort value-added productivities $logA_{is}^{v}$ in its first and second moments. Proposition 1 suggests that when the intermediate input distortion is orthogonal with the true productivity, the average downward bias of $logA_{is}^{v}$ is independent with the true productivity level. The firm-level difference between $K_{is}^{eff,v}$ and K_{is}^{eff} then only depends on the dispersion of τ_{is}^{m}. When the dispersion increases, the dispersion of $logA_{is}^{v}$ conditional on $logA_{is}$ also increases, which leads to a larger gain under the HK approach (*second-order effect*). This result has been emphasized in Hang et al. (2020). Nevertheless, with a strong degree of size-dependency of distortions, the first-order effect in Proposition 1 could dominate.

This mechanism is important when we compare industries above and below the 45-degree line. The two groups have a similar average within-industry dispersion of τ_{is}^{m}, 0.19. However, for the above group, the within-industry correlation coefficient between intermediate input distortions and productivities averages 0.27. For the below group, the coefficient averages 0.12. Figure 3 plots the average of τ_{is}^{m} away from the industry-level means across deciles of true productivities. One could see a steeper line for the above group, with τ_{is}^{m} ranging from 0.05 below the industry-level means to 0.15 above when we move $logA_{is}$ from the 1st to the 10th decile. As a result, in Figure 4, the average $(K_{is}^{eff,v} - K_{is}^{eff})/K_{is}^{eff}$ curve of the above group has a steeper drop for the top 10% productive firms, compared to that of the below group. The same analysis applies to labor and consequently, the value-added output from the production function.

To conclude, this section shows the need to understand size-dependent intermediate input distortions in the Chinese data. We are aware that absent intermediate input distortions, results above still hold if there are size-dependent output market distortions (e.g., firm-level markups in De Loecker and Warzynski (2012)) by their inseparability in equation (3). To disentangle the role of intermediate input distortions, we provide direct evidence on two specific frictions that can be size-dependent in the next section.

2 Direct Evidence on Intermediate Input Frictions

This section aims to provide empirical evidence on two specific intermediate input frictions: pay-in-advance and financial frictions. Industries with a longer pay-in-advance have larger dispersions of marginal revenue products of intermediate inputs.

The dispersion decreases when the financial market is developed, especially for industries that are financially vulnerable with a longer pay-in-advance.

2.1 Pay-in-Advance

A large body of literature in trade, corporate finance, and international finance studies how the time interval between purchasing materials and the collection of revenue affects firms' performance (e.g., Ramey, 1989; Petersen and Rajan, 1997; Antras and Foley, 2015). We use DI and CCC to represent this pay-in-advance time arrangement in production (Raddatz, 2003):

$$DI = \frac{\text{Inventory}}{\text{Sales}} \times 365 \tag{13}$$

$$CCC = (DI + \frac{\text{Account Receivable}}{\text{Sales}} - \frac{\text{Account Payable}}{\text{COGS}}) \times 365 \tag{14}$$

where $COGS$ is the cost of goods, i.e., the sum of the intermediate input costs and the wage payment to production workers. DI reflects inventory holdings for production, with the Just-in-Time to be one extreme. CCC further includes a firm's net trade credit position with its suppliers and customers. The former is our preferred measure of pay-in-advance by its technological nature.

Table 1 reports averages of industry-level median DI and CCC for both China and the U.S. In the ASIF data, a median firm for an average industry maintains an 44-day inventory and a 6-day net trade credit. The level of DI is close to one month reported by firms in the World Bank Enterprise Survey (WBES, 2012) for their most important materials.

The DI and CCC are longer for listed firms: 84 and 116 days for China and 62 and 107 days for the U.S., respectively. The difference in DI between the listed and the ASIF firms suggests that inventory holdings could be distorted by market imperfections for firms of different sizes. Similarly, the difference in CCC reflects the disproportionate role of large firms in issuing net trade credit (e.g., Petersen and Rajan, 1997). To alleviate the bias caused by distortions on these measures, we adopt the U.S. levels of DI and CCC for later analysis, viewing them as undistorted and technological for the production of each industry.

How does the pay-in-advance time length correlate with the intermediate input misallocation across industries? Figure 5 suggests that for both measures of DI and CCC, the longer the pay-in-advance length for an industry, the larger its coefficient of variation of $logMRPM_{is}$. This fact could be mechanically due to an ex-post sub-optimal level of intermediate inputs determined before productions, similar to the time-to-build nature of capital. It could also be the high demand for working capital needed to finance the pay-in-advance purchase and firms are thus constrained. We explore the latter possibility in the next subsection.

2.2 Financial Frictions

We first investigate whether marginal returns of intermediate inputs and capital decrease as firms get older and larger, motivated by studies of Cooley and Quadrini (2001) and Arellano et al. (2012). If financial frictions exist, younger and smaller firms would use fewer inputs and have higher returns. Figure 6 plots the 25th, 50th, and 75th percentiles of $r_{logMRPM}$ at each age and asset decile, where $r_{logMRPM}$ is the residual from regressing $logMRPM$ on state-owned enterprise (SOE) and exporter dummies, and year and industry fixed effects (FE). The plot shows that different percentiles of marginal returns of intermediate inputs indeed decrease with both size and age, consistent with the financial friction story. The plot for capital returns is similar (see Figure A2 in the appendix), consistent with the importance of financial frictions on capital extensively studied in the literature.

To further quantify the financial friction, we exploit provincial differences in the financial market development in China and investigate if the financial development disproportionately lowers the dispersion of marginal returns for financially vulnerable industries. We follow Raddatz (2003), Tong and Wei (2011), and Manova (2013) and use the asset tangibility, $AssetTang$, and the external finance dependence, $ExtFin$, to proxy the vulnerability of each industry. Meanwhile, an industry with its production technology that features a longer period of inventory holding (DI) requires more liquidity and thus is more likely to be constrained, *given the same tangible asset for collateral ($AssetTang$) and external financing need ($ExtFin$)*. For the CCC measure, it is less certain whether a higher CCC poses more constraints. The reason is that a longer CCC may suggest not only a longer pay-in-advance but also a stronger capability of trade credit issuance due to an easy access to receivable financing from the financial sector (Shao, 2017). We construct the variable NTC as CCC net DI to directly reflect the net trade credit.

For measures on the province-level financial development, we use $LoanMkt_{pt}$ and $DepMkt_{pt}$ from the NERI Indices of Marketization of China's Provinces.[15] The former is based on the provincial fraction of loans lent to non-state owned firms and the latter on the provincial fraction of deposits held by non-state owned banks, both of which were first scored on a 0 to 10 scale in 1997 (see Table A3 and A4 in the appendix for details). We prefer these indices to the private credit to GDP ratio since the latter could represent an inefficient credit allocation across provinces rather than the quality of provincial financial markets. For example, during this period, Beijing had the highest loan-to-GDP ratio (195%). However, it was ranked 24th in the $LoanMkt$ index and 15th in the $DepMkt$ index among 29 provincial regions with non-missing values.

The following regression for industry s and province p tests the financial friction story

$$\begin{aligned}SdMRPM_{spt} = {} & \beta_0 + \beta_1 AvgMRPM_{spt} + \beta_2 FinDevp_{pt} + \beta_3 FinDevp_{pt} \times AssetTang_s + \\ & \beta_4 FinDep_{pt} \times ExtFin_s + \beta_5 FinDep_{pt} \times DIHi_s + \beta_6 FinDep_{pt} \times NTCHi_s + \\ & \beta_7 FinDep_{pt} \times AssetTang_s \times DIHi_s + \beta_8 FinDep_{pt} \times ExtFin_s \times DIHi_s + \\ & \beta_9 FinDep_{pt} \times AssetTang_s \times NTCHi_s + \beta_{10} FinDep_{pt} \times ExtFin_s \times NTCHi_s + \\ & \beta_X X_{spt} + \epsilon_{spt} \end{aligned} \tag{15}$$

where $SdMRPM_{spt}$ and $AvgMRPM_{spt}$ are dispersions and averages of $logMRPM$, respectively, within each industry-province cell in year t. $DIHi_s$ is a dummy that equals 1 if DI_s is above the average across industries and 0 otherwise. $NTCHi_s$ is similarly defined. Other control variables X_{spt} include shares of state-owned firms and exporting firms, industry FE, province FE, and year FE. Coefficients of interests are those for $FinDep_{pt}$ and its double and triple interaction terms with industry-level measures.

Table 2 presents regression results with standard errors clustered within industry-province cells. We drop cells with fewer than 10 firms (15% of observations) to avoid small sample biases and cells from Tibet by its lack of development indices before 2000. Columns (1) - (3) use $LoanMkt_{pt}$ as the financial market development

[15]Firstly published in 1997, the NERI indices are updated every three years. They cover five aspects of the marketization of provincial economies: relations between the government and markets, developments of the non-state owned economies, product markets, factor markets, and legal and accounting service markets.

index, while columns (4) - (6) use $DepMkt_{pt}$. Columns (3) and (6) also include $CV(MRPK)_{spt}$ to control for the effect of capital misallocation on intermediate input misallocation. Across industry-province cells, the average standard deviations are 0.2365 for $logMRPM$ and 1.3459 for $logMRPK$ during this time period.

Results are summarized as follows. First, across all columns, an industry with a lower asset tangibility has a larger drop in the intermediate input misallocation from the financial market development. Specifically, for industries with an asset tangibility measure 1 standard deviation (0.1241) below the average, a one standard deviation increase in $LoanMkt$ (3.42) decreases $SdMRPM_{sp}$ by an additional 0.0068 (3% of its average level) in columns (1) - (3), and a one standard deviation increase in $DepMkt$ (2.44) decreases $SdMRPM_{sp}$ by an additional 0.0020 (1% of its average level) in columns (4) - (6). This finding also exists for industries with a higher external finance dependence despite statistically insignificant coefficients.

Second, the financial market development benefits industries with a longer DI by lowering intermediate input misallocation more. Columns (1) and (4) seem to suggest that industries with a higher DI and NTC benefit less from the financial market development. However, when the triple interaction terms are included in columns (2), (3), (5), and (6), the coefficient of $FinDevp * DIHi$ becomes negative, though insignificant. For triple interactions, results suggest that the effect of financial market development on lowering intermediate input misallocation is stronger for industries with more days on inventory than the average. For the $DIHi = 1$ group in column (2), the coefficient of $FinDevp * AssetTang$ is 0.0665 (0.0206 + 0.0459) and that of $FinDevp * ExtFin$ is -0.0221 (-0.0026 - 0.0195), in comparison to 0.0206 and -0.0026, respectively, for an average industry. These numbers suggest that a one standard deviation increase in $LoanMkt$ decreases $SdMRPM_{sp}$ by 10% of its average level for industries with a DI higher than the average *and* an asset tangibility measure one standard deviation lower than the average. The decrease is 8.6% for industries a DI higher than the average *and* an external finance dependence measure one standard deviation higher than the average. Qulitatively similar results hold if we use the $DepMkt$ as the financial market development index.

Third, the financial market development further benefits industries with lower net trade credit by lowering their intermediate input misallocation more. A higher net trade credit position suggests a longer time to collect revenue and a higher need for working capital. However, it could also be an endogenous outcome because of the easier access of these industries for receivable financing (Shao, 2017), with examples including pharmaceuticals and electric equipment. Overall, results in Table 2 suggest that the latter mechanism dominates and financial market development benefits industries with a lower NTC more.

Finally, Table 2 shows that intermediate input misallocation increases when there are more state-owned firms. The financial friction results barely change when we include the dispersion of $logMRPK_{sp}$ as another control. For robustness checks, Table A4 in the appendix uses continuous DI and NTC and shows similar results. Table A5 shows how the financial development across provinces decreases capital misallocation disproportionately for financially vulnerable industries.

In summary, this section provides empirical evidence on two intermediate input frictions: pay-in-advance and financial frictions. They may interact with capital frictions in generating the reduced-form wedges in equation (3). For instance, for financially constrained firms, the trade-off between capital and working capital investment (Fazzari and Petersen, 1993) induces wedges in $MRPK$ and $MRPM$ simultaneously. Thus, the role of intermediate input frictions in shaping misallocation could manifest themselves through the dispersion of $MRPK$. The next section hence introduces a quantitative model to endogenously generate these wedges and to understand the role of each friction in shaping misallocation. Meanwhile, the model also answers the question whether the two intermediate input frictions can explain, at least partly, why the HK apporach underestimates misallocation.

3 Model

This section incorporates pay-in-advance and financial frictions on intermediate inputs into a standard industry dynamics model of Hopenhayn (1992) to quantify their roles in accounting for misallocation. The model is closest to Cooley and Quadrini (2001) and Arellano et al. (2012), where firms endogenously default and their borrowing interest rates reflect this default risk.

3.1 Firms

The infinite-horizon economy is populated with a mass of firms, $\mathbb{M}_t$, which grows over time at a rate of g. Here a period represents a year. All firms are from a representative industry. We focus on how intermediate input frictions cause misallocation in a partial equilibrium framework instead of the general equilibrium propagation studied in the literature (see, e.g., Jones, 2011; Hang et al., 2020; Liu, 2019; Baqaee and Farhi, 2020; Osotimehin and Popov, 2020).

Given an exogenous productivity, a firm is a decreasing-return-to-scale technology that transforms intermediate inputs, capital, and labor into the gross-output revenue. The revenue production function for firm i at time t is

$$P_{it}Y_{it} = exp(z_{it})K_{it}^{\tilde{\beta}_k(1-\beta_m)}L_{it}^{\tilde{\beta}_l(1-\beta_m)}M_{it}^{\tilde{\beta}_m} \tag{16}$$

where $\tilde{\beta}_k = \frac{\sigma-1}{\sigma}\beta_k$ and $\tilde{\beta}_l = \frac{\sigma-1}{\sigma}(1-\beta_k)$. The function is the same as the revenue production function in Section 2 with the industry superscript dropped here. In the quantitative analysis, we follow the data section and impose a CES industry-level aggregation to perform the reallocation exercise. The level of misallocation is not affected whether we model firms as quantity or revenue producers, since productivity z_{it} only differs from the log quantity one by a constant term $logP_sY_s^{\frac{1}{\sigma}}$ in the stationary firm size distribution.

Firm-level productivity z_{it} has a permanent component $\bar{z}_i$, $\bar{z}_i \sim N(\mu_{\bar{z}}, \sigma_{\bar{z}}^2)$, and a transitory component μ_{it} that follows an AR(1) process with persistence ρ

$$\mu_{it+1} = \rho\mu_{it} + \epsilon_{it+1}, \epsilon_{it+1} \sim N(0, \sigma_\epsilon^2) \tag{17}$$

Given productivity z_{it}, capital K_{it}, and intermediate inputs M_{it}, firms choose labor input L_{it} to maximize their gross output net of labor payment, π_{it}:

$$\pi_{it} = \max_{L_{it}} P_{it}Y_{it}(z_{it}, K_{it}, M_{it}, L_{it}) - wL_{it} \tag{18}$$

where P_{it} is the output price and w is the wage. Labor input is determined intra-period without frictions.

Pay-in-Advance At time t, firms pay $\omega < 1$ fraction for the next period intermediate input M_{it+1} at the same time when they set capital K_{it+1}. The rest, $1-\omega$ fraction, is paid at time $t+1$. The timing arrangement is similar to the international finance literature (e.g., Neumeyer and Perri, 2005; Mendoza and Yue, 2012) which models labor payments to be paid in advance to create firms' working capital need.

At $t+1$, if the realization of z_{it+1} is low, the pre-determined M_{it+1} could be too high. In this case, firms choose the usage of intermediate inputs, $\tilde{M}_{it+1} < M_{it+1}$, to maximize their profit and sell the extra, $M_{it+1} - \tilde{M}_{it+1}$. In the opposite case, if the pre-paid intermediate inputs level M_{it+1} is too low to be optimal in a high productivity realization, firms cannot adjust the intermediate inputs beyond M_{it+1}. In other words, firms choose $\tilde{M}_{it+1} \leq M_{it+1}$ to maximize Π_{it+1}

$$\Pi_{it+1} = \max_{\tilde{M}_{it+1} \leq M_{it+1}} \pi_{t+1}(z_{it+1}, K_{it+1}, \tilde{M}_{it+1}) - (1-\omega)M_{it+1} + (M_{it+1} - \tilde{M}_{it+1}) \tag{19}$$

One may think the environment rigid since firms are disabled from holding intermediate inventories that allow them to set $\tilde{M}_{it+1} > M_{it+1}$. However, if we model the inventory holding decision, its increment again needs to be financed by working capital due to the pay-in-advance nature. The key is that uncertainty exists and there is always a chance that the pre-determined M_{it+1} or inventory is ex-post sub-optimal with a high productivity realization.[16]

Financial Frictions Similar to Cooley and Quadrini (2001) and Arellano et al. (2012), we model financial frictions as costly equity and debt issuances.

Entrepreneurs first incur a cost of c_e for each unit of new equity issuance. Second, when they borrow, there is a limited enforcement problem. As detailed later, the price of bond $q_{it}(z_{it}, B_{it+1}, K_{it+1}, M_{it+1})$ decreases with the expected default probability, implying a higher interest rate of borrowing. In the special case with a zero default probability, debt price $q_{it} = \frac{1}{1+r_2}$ where r_2 is the risk-free borrowing rate. The rate r_2 exceeds the saving rate r_1 by assuming a per-dollar intermediation cost of c_I.

With frictions specified above, the end-of-period dividend D_{it} is

$$\begin{aligned} d_{it} &= \Pi_{it}(z_{it}, K_{it}, M_{it}) - (K_{it+1} - (1-\delta)K_{it}) - C(K_{it}, K_{it+1}) - \frac{1}{1+r_1}\omega M_{it+1} - \\ &\quad B_{it} + q_{it}(z_{it}, B_{it+1}, K_{it+1}, M_{it+1})B_{it+1} && (20) \\ D_{it} &= (1 + \mathbb{1}(d_{it} < 0)c_e)d_{it} && (21) \end{aligned}$$

where $C(K_{it}, K_{it+1})$ is the capital adjustment cost that equates to $\xi K_{it} + \frac{\theta}{2}(K_{it+1} - K_{it})^2/K_{it}$.

[16] The productivity estimation literature, i.e., Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2015), and Gandhi, Navarro, and Rivers (2017), builds on the assumption that part of the productivity shock occurs after firms' choosing intermediate inputs.

Value Functions and Default For simplicity, the rest of the model is in a recursive form and abstracts away the firm subscript i.

At the beginning of each period, a firm chooses to default or repay after the realization of z. Given the state variables (z, B, K, M) and the bond price schedule $q'(z, B', K', M')$, the value of repayment is

$$V^r(z, B, K, M) = \max_{B', K', M'} D + \beta(1-\psi)E_{z'|z}V(z', B', K', M') \tag{22}$$

and the value of default is

$$V^d(z, B, K, M) = \max_{B', K', M'} D^d + \beta(1-\psi)E_{z'|z}V(z', B', K', M') \tag{23}$$

$$s.t. D^d = (1 + \mathbb{1}(d^d < 0)c_e)d^d \tag{24}$$

$$d^d = -\frac{1}{1+r_1}\omega M' - K' - C(0, K') + q(z, B', K', M')B' \tag{25}$$

In other words, once default, the firm loses its capital K and the fraction of intermediate inputs it has paid ωM and thus generates zero revenue at time t. The unpaid intermediate inputs, $(1-\omega)M$, is returned back to suppliers without a repudiation cost for simplicity.

By equation (23), we allow default when firms continue operations. After the default decision, the firm is subject to an exogenous exit shock with a probability ψ. With equations (22) and (23), the value function $V = \max\{V^r, V^d\}$ and the default variable χ equals to 1 if $V = V^d$ and 0 otherwise.

3.2 Entrants

In each period t, there are $\mu_{ent}\mathbb{M}_t$ mass of entrants. Each entrant draws an initial permanent productivity $\bar{z}$ from a distribution $N(0, \sigma_z^2)$ and a transitory productivity μ_0 from another distribution $N(0, \sigma_\mu^2)$. The entrant also draws an initial wealth $B_0 < 0$ independently from a Pareto distribution with the density function $g(-B_0)$:

$$g(-B_0) = \begin{cases} \frac{\alpha a_{\min}^\alpha}{(-B_0)^{\alpha+1}} & if - B_0 \geq a_{\min}, \\ 0 & if - B_0 < a_{\min}. \end{cases} \tag{26}$$

where a_{min} is the minimum wealth.

Firms do not enter and produce right away. There exists a preparation period for entrants to build up capital stock and intermediate inputs out of scratch, according to their initial productivity $z_0 = \bar{z} + \mu_0$ and wealth draw B_0. Their choices of borrowing $B'_{ent}(z_0, -B_0, 0, 0)$, capital $K'_{ent}(z_0, -B_0, 0, 0)$, and intermediate inputs $M'_{ent}(z_0, -B_0, 0, 0)$ for the first production period are given by maximizing the value function $V^e(z_0, B_0, 0, 0)$

$$V^e(z_0, B_0, 0, 0) = \max_{B', K', M'} D^e + \beta(1-\psi)E_{z'|z_0}V(z', B', K', M') \tag{27}$$

$$s.t. D^e = (1 + \mathbb{1}(d^e < 0)c_e)d^e \tag{28}$$

$$d^e = -\frac{1}{1+r_1}\omega M' - K' - B_0 + q(z, B', K', M')B' \tag{29}$$

We assume no capital adjustment costs for entrants.

3.3 Financial Intermediaries

There exists a continuum of risk-neutral competitive intermediaries that take deposits and lend. Given debt price functions $q'(z, B', K', M')$, the problem for a competitive lender is to choose a supply function $B'^s = B'^s(z, K', M'; q')$ to maximize its expected profit:

$$\begin{aligned}\max_{b'}(1-\psi)\{(1 - E_{z'|z}\chi')B' + E_{z'|z}(\chi' \min\{B' - \gamma_2\omega M' \\ - [\gamma_1(1-\delta) - \xi]K', 0\})\} - (1 + r_1 + c_I)q'B'\end{aligned} \tag{30}$$

The first term here presents debt repayment B'^s with a probability $(1-\psi)(1 - E_{z'|z}\chi')$. The second term gives an expected loss when the borrower defaults, in which case the intermediary recovers γ_1 of the undepreciated capital net of a fixed adjustment cost and γ_2 of intermediate inputs the borrower has paid.

3.4 Equilibrium

A recursive equilibrium is a debt price function $q'(z, B', K', M')$, policy functions of incumbent firms $B'^d(z, B, K, M; q')$, $K'(z, B, K, M; q')$, and $M'(z, B, K, M; q')$, a transition indicator function for incumbents $\mathbb{T}(z, B, K, M; B', K', M')$, policy functions of entrants $B'_{ent}(z_0, -B_0, 0, 0; q')$, $K'_{ent}(z_0, -B_0, 0, 0; q')$, and $M'_{ent}(z_0, -B_0, 0, 0; q')$, a default rule $\chi(z, B, K, M)$, a transition indicator function for entrants $\mathbb{T}_{ent}(z, B, 0, 0; B', K', M')$, a supply function of funds $b^s(z, K', M'; q')$, a debt price function $q'(z, B', K', M')$, an endogenous mass of firms M', and a probability density function of firms $f'(z', B', K', M')$ such that

1. given the debt price function $q'(z, B', K', M')$, policy functions of $B'^d(z, B, K, M; q')$, $K'(z, B, K, M; q')$, and $M'(z, B, K, M; q')$, and the default rule $\chi(z, B, K, M)$ solve the problem of incumbent firms. Policy functions of $B'_{ent}(z_0, -B_0, 0, 0; q')$, $K'_{ent}(z_0, -B_0, 0, 0; q')$, and $M'_{ent}(z_0, -B_0, 0, 0; q')$ solve the problem of entrant firms;

2. given the debt price function $q'(z, B', K', M')$, the supply function of funds $B^s(z, K', M'; q')$ solves the lenders' problem;

3. the debt price function $q'(z, B', K', M')$ clears the supply and the demand of funds at the firm-level, if $B' > 0$:

$$\mathbb{T}(z, B, K, M; B', K', M')B'^d(z, B, K, M; q') = B'^s(z, K', M'; q') \text{ for incumbents} \tag{31}$$

and

$$\mathbb{T}_{ent}(z, B_0, 0, 0; B', K', M')B'^d_{ent}(z, B, 0, 0; q') = B'^s(z, K', M'; q') \text{ for entrants} \tag{32}$$

4. the distribution f' and the mass of firms $\mathbb{M}'$ evolve recursively as in equations (33), (34), and (35), given an initial mass $\mathbb{M}_0$, an initial firm distribution f_0, a mass of entrants μ_{ent}, a default rule $\chi(z, B, K, M)$, and policy functions of incumbents and entrants:

$$f'(z', B', K', M') = \mu_{ent} \int_z \int_B \phi(z) g(-B) \mathbb{T}_{ent}(z, B, 0, 0; B', K', M') dz dB + (1 - \psi) \\ \int_z \int_B \int_K \int_M (1 - \chi'(z', B', K', M')) f(z, B, K, M) \mathbb{T}(z, B, K, M; B', K', M') \phi(z'|z) dz dB dK dM \tag{33}$$

$$f'(z', 0, 0, 0) = \int_z \int_B \int_K \int_M \chi'(z', B', K', M') f(z, B, K, M) \mathbb{T}(z, B, K, M; B', K', M') \\ \phi(z'|z) dz dB dK dM \tag{34}$$

$$\mathbb{M}' = \mathbb{M}(1 + \mu_{ent} - \psi) \tag{35}$$

where $\phi(z'|z)$ is the conditional probability according to the AR(1) process. A stationary distribution is defined as $f'(z, B, K, M) = f(z, B, K, M)$ for any state (z, B, K, M).

In summary, this section studies a quantitative model in which firms are financially constrained in capital and intermediate inputs, because of costly equity and debt issuances. Firms need to finance intermediate inputs because of the pay-in-advance timing requirement. The next section disciplines the model using the Chinese data, in order to understand whether intermediate input frictions help to explain why the HK approach underestimates misallocation and the quantitative role of each friction in shaping misallocation.

4 Quantitative Analysis

This section implements quantitative analysis. We describe how we parametrize our model, introduce the mechanism of financial frictions, compare measures of misallocation under the HK and GO approaches, and decompose misallocation generated by each friction in the model. We find that in the model simulated data, the HK approach also underestimates the misallocation by the size-dependent financial frictions on intermediate inputs. We also find that a larger role of financial friction in generating misallocation when firms are also financially constrained in intermediate inputs.

4.1 Parametrization

We first introduce the mapping between the model and the data. The number of firms in the manufacturing sector in China is 1.26 million in 2004 (Economic Census) and only 0.25 million (20%) of them are in the ASIF data by the minimum sales requirement.[17] Thus, we simulate firms from the model implied stationary distributions and obtain the top 20% sub-sample in sales as the model analog of the ASIF data, which we calibrate our model to. In the simulated data, intermediate inputs usage $\tilde{M}$, not the pre-paid level M, corresponds to the observed firm-level intermediate inputs in the ASIF data.

In terms of parameters, we parametrize the cost of equity issuance $c_e = 0.3$ as in Cooley and Quadrini (2001). The capital adjustment cost is parametrized

[17] See Table A6 in the appendix for more details.

by $\xi = 0.039$ and $\theta = 0.049$ following Cooper and Haltiwanger (2006). Capital deprecation rate δ equals to 0.09. Firms' discount factor β is 0.94, which implies a risk-free borrowing interest rate $r_2 = 0.06$ according to People's Bank of China (PBOC) annual reports over 1998 - 2007. Similarly, the saving interest rate r_1 equals 0.03 to match the average deposit rate. The exit rate ψ is 0.08 to match the average exit rate during 2008 - 2012 according to a firm survival analysis report by the State Administration for Industry and Commerce of China (SAIC).[18] Given these values, we have $\beta(1-\psi)(1+r_2) < 1$ that ensures unconstrained firms invest efficiently as in Arellano et al. (2012).

In the gross-output production function, the intermediate input share $\tilde{\beta}_m$ is 0.61 following Jones (2011) and the value-added labor and capital shares are both 0.5 as in Section 2. We then calibrate the return-to-scale parameter η to match the fact that 84.5% of total gross output is produced by the top 10% firms in sales in the manufacturing sector, which are equivalently the top 50% firms in the ASIF data. The rationale is that as η increases, gross output in the economy is more concentrated within the largest firms. This gives $\eta = 0.85$. The annual growth rate in the manufacturing population during this period is approximately 9%, according to the economic censuses of 2004 and 2008. Combined with the exit rate, the relative mass of entrants μ_{ent} is thus 17%. We set the threshold sales y_c such that the fraction of firms with sales greater than y_c is 20%.

Capital and intermediate input recovery rates, γ_1 and γ_2, determine how binding the borrowing constraint is. Inspired by Bai et al. (2018), we calibrate γ_2 to match the level of leverage (i.e., debt-over-asset) and γ_1 to match its slope with respect to asset percentiles in the ASIF data.[19] In the model, the leverage ratio is defined as debt over the sum of capital and the pre-paid intermediate inputs. Our numerical experiments find that the leverage level is sensitive to γ_2 and its slope with asset sensitive to γ_1. This gives us $\gamma_1 = 0.60$ and $\gamma_2 = 0.10$.

The productivity process is calibrated to match the productivity moments in the ASIF data. We discretize the permanent productivity $\bar{z}_i$ into 5 grids, and the transitory productivity μ_{it} into 15 grids, using Tauchen (1986)'s method. The persistence of transitory productivity ρ and its standard deviation are chosen to match

[18]Entries and exits in the ASIF data cannot be viewed as births and deaths of firms by its left-truncation in the firm sales distribution.

[19]Using log sales as the firm size measure, a corporate finance literature (e.g., Rajan and Zingales, 1995; Booth, Aivazian, Demirguc-Kunt, and Maksimovic, 2001) also finds the positive cross-sectional size-leverage relationship in developing and developed countries.

the one-period persistence and the cross-sectional dispersion of productivities in the data. The mean and standard deviation of the permanent productivity distribution are jointly calibrated to match the average and the 5-year period persistence of firm-level productivities in the data.

For entrants, the productivity distribution of entrants is the same as that of incumbents. The shape parameter α and minimum wealth a_{min} of the initial wealth distribution determine the first-period output for entrants. The fraction of intermediate inputs paid a period ahead ω impacts how fast a firm grows post entry and the relative market share over different ages. Thus, the three parameters, namely, α, a_{min}, and ω are jointly determined to match the facts that 6.94% of newly-established firms younger than five years old have sales greater than y_c, that these firms are 65.56% of an average ASIF firm in sales, and that 37.09% of ASIF entrants are older than five over a 5-year period in the data.[20] The level of $\omega = 40\%$ is close to the CCC in U.S. Compustat data (0.29 years).[21]

Table 3 lists all parameters and their values, and Table 4 shows the differences of moments between the model and the data. The model overall well replicates the data in targeted moments, except for the market share of top 10% firms, which is generally a moment hard to match. In addition, the model is also close to the data in the following five non-targeted moments: (i) the slope regressing intermediate inputs usage and gross-output ratio (%, $\frac{\tilde{M}}{Y}$) on the asset percentiles; (ii) the slope regressing capital and gross-output ratio (%, $\frac{K}{Y}$) on the asset percentiles; (iii) the standard deviation of interest rates; (iv) the coefficient of variation for $logMRPM$; (v) the coefficient of variation for $logMRPK$.

4.2 Financial Frictions: Roles of c_e, γ_1, and γ_2

This subsection illustrates the mechanism of financial frictions via comparative statics of c_e, γ_1, and γ_2. We choose statistics that reflect the financial condition, the equilibrium size, and the marginal revenue product statistics of firms in the top 20%

[20]The ratios of 37.09% and 65.56% are averages for two time periods, 1998-2003 and 2002-2007 (see Table A7 in the Appendix). The ratio of 6.94% equals 66,221 firms younger than five years old in the 2003 ASIF data, divided by the total number of newly-established firms over five years. This total number is estimated as 953,388, assuming a 17% entry rate, an 8% exit rate, and that the ASIF data also constituted the top 20% manufacturing firms in 1998.

[21]We do not use DI to pin down ω as it does not include the time length between the cash outlay of material purchases and its arrival into the warehouse. It also does not include the time to sell goods and collect revenues.

sub-sample of our simulated data.

Role of c_e We firstly set c_e to two alternative levels, 0 and 1. Table 5 shows that as the cost of equity issuance increases from 0 to 1, the equilibrium fraction of firms that issue new equity decreases from 80.06% to 73.35%. Simultaneously there is an increasing fraction of firms default. The average leverage ratio decreases from 0.57 to 0.36, consistent with Bolton, Wang, and Yang (2021) which argues that a costly equity issuance decreases firms' capacity to borrow. Meanwhile, the correlation between the leverage and the asset percentile increases with c_e, reflecting the increasing importance of assets in debt financing when equity becomes costly. As a result, the capital stock for an average firm decreases substantially from 874.61 to 360.92. In addition, misallocations of capital and intermediate inputs increase with increasing standard deviations of marginal products, from 0.15 to 0.25 for intermediate inputs and from 0.36 to 0.72 for capital.

Role of γ_1 We secondly change the capital recovery rate into two other levels, 0 and 1. Table 5 shows that when the recovery rate increases from 0 to 1, the fraction of firms with new equity issuance increases from 72.16% to 77.50%. The fraction of firms default is 0 when $\gamma_1 = 0$ because the leverage decreases to a lower level of 0.45. Meanwhile, since capital plays no role as collateral when $\gamma_1 = 0$, the leverage(%)-asset slope is -0.16, reflecting a greater need to borrow when firms are small. This slope increases to 0.35 when capital becomes the perfect collateral, i.e., $\gamma_1 = 1$. In equilibrium, the average capital increases from 459.63 to 674.08. The average of $MRPK$ decreases from 0.50 to 0.36 with a decreasing standard deviation from 0.46 to 0.37, suggesting that capital misallocation is smaller when the capital recovery rate is higher. The result is the opposite for $MRPM$. When γ_1 increases from 0 to 1, the average and standard deviation of $MRPM$ increases because firms invest more in capital than intermediate inputs.

Role of γ_2 Moment changes by varying γ_2 are fairly similar to those of γ_1. We simplify our exposition by summarizing as follows: (i) the change of leverage ratio is more sensitive to γ_2 while the leverage(%)-asset slope is more sensitive to γ_1; (ii) the average and standard deviation of $MRPM$ are not sensitive to γ_2, suggesting that once there is a working capital constraint, the key parameter to determine its misallocation is the cost of equity and the capital recovery rate.

4.3 The In-equivalence in the Model

With calibrated parameters, we simulate a 5-year unbalanced panel of 310,240 firms, with ages ranging from 1 to 21 by the entry and exit process. Given this simulated data, we answer the following questions: (i) does the HK approach also underestimate the measured misallocation in the model? (ii) how do the model-generated size-dependent distortions compare to that in the Chinese ASIF data?

Using equations (11) and (12), we re-do the reallocation exercises under both approaches in the model simulated data. Results show that the value-added of the representative industry in our model could increase by 45% if we follow the HK approach and view firms as value-added producers. This number is lower than the gain of 69% from the GO approach, where firms are viewed as gross-output producers. In other words, the model replicates the fact of a smaller measured misallocation by the HK approach in the Chinese ASIF data.

Further, the model replicates the size-dependent nature of intermediate input distortions in the ASIF data. Table 6 shows the model-data comparison in correlations and dispersions of productivities and distortions. For intermediate input distortions, the correlation with true productivities is 0.27 in the ASIF data and 0.49 in the model simulation. Similarly, the correlation between capital distortions and true productivities is 0.58 in the ASIF data and 0.56 in the model simulation. Size-dependent features of both input distortions are generated by the financial friction in the model and, at least partly, in the ASIF data according to our direct evidence in Table 2. However, we over-predict the correlation between capital and intermediate input distortions. In the model, the correlation coefficient is 0.19 and higher than the number -0.01 in the ASIF data. The difference is possibly due to other distortions, such as enforcement frictions in the delivery of intermediate goods (Boehm and Oberfield, 2018) and government subsidies for industrial policies (Liu, 2019). Additionally, Table 6 also finds that dispersions of value-added quantity and revenue productivities are larger than those of the gross-output ones in both the ASIF data and the model simulation, consistent with Gandhi et al. (2017) and Hang et al. (2020).

To further rationalize the underestimated result in the model, we plot the downward deviations of value-added productivities and capital in the model simulation compared to those in the ASIF data. Figure 7 shows that the model replicates the right half of the hump-shaped $E(\Delta log A^{v})$ curve in the ASIF data. For the plot over deciles of intermediate input distortions, the model also replicates the level of downward bias for the most 40% distorted firms. When we plot $E(\Delta log A^{v})$ over the decile of true productivities, however, the level of bias in the model falls short compared to that in the ASIF data. Furthermore, the model lacks mechanisms of negative intermediate input distortions, which explains why the model cannot generate the left half of the hump-shaped $E(\Delta log A^{v})$ curve.

Since most productive firms have disproportionately biased value-added productivities, they also receive fewer capital $K_i^{eff,v}$ under the HK approach in the model simulation. Figure 8 illustrates this point. For the top 10% productive firms, $(K_i^{eff,v} - K_i^{eff})/K_i^{eff}$ in the model averages -1.7%, compared to -4% in the ASIF data. The $E[(K_i^{eff,v} - K_i^{eff})/K_i^{eff}]$ curve exhibits a steeper slope from the 1st to the 9th decile of true productivities $log A_{is}$ in the model simulation, because the firm size distribution is more concentrated to the right compared to that in the ASIF data. The same analysis can be extended to labor and consequently, the value-added output from the production function.

4.4 Complementarity in Misallocation

Given the in-equivalence result, this subsection shows how distorted intermediate inputs and value-added complement with each other in shaping the measured misallocation. To do so, we compute gross-output and value-added gains by (i) reallocating intermediate inputs alone; (ii) reallocating capital and labor alone; (iii) reallocating all three inputs together (see the appendix for math details of exercises (i) and (ii)). We also show the performance of the model in matching these gains in the ASIF data.

We first discuss the case of reallocating intermediate inputs alone. In the *Top 20%* sub-sample, this exercise gives a gross-output gain of 3.40% and a value-added gain of 8.88%, respectively, close to the gains of 3.24% and 12.72% in the ASIF data. According to the reallocation gain for *All firms*, Table 7 also suggests a slightly higher magnitude of intermediate input misallocation in China's manufacturing sector than that in the ASIF data.

Second, in the model simulation, reallocating capital and labor increases the gross output by 8.60% and the value added by 22.13% for the *Top 20%* sub-sample. These numbers are also close to 11.36% and 46.15% in the Chinese ASIF data. Again, we find that the output gains for all firms are higher than those in the top 20%

sub-sample in the model simulation.

Third, for the reallocation of three inputs, Table 7 shows potential gains of 26.76% in gross output and 68.62% in value-added in the model simulated *Top 20%* sub-sample. These two numbers are much larger than the sum of gains from reallocating intermediate inputs alone and reallocating capital and labor alone. This result is qualitatively unsurprising by the Cobb-Douglas production function we impose. It, however, informs us that despite a small gain of reallocating intermediate inputs alone, the distortion of intermediate inputs magnifies its impact on the overall gains via the input complementarity. In other words, in exercise (ii), the post-reallocation firm-level capital and labor differ from the efficient levels because intermediate inputs are kept distorted.

Lastly, Table 7 suggests that the model accounts for 71% of the measured misallocation in the ASIF data in gross output and 43% in value added. The discrepancy between the two percentages arises from a higher intermediate input revenue share in several industries in the ASIF data, such as electronic and telecommunications (0.73) and petroleum refining (0.76).

4.5 Decomposing Misallocation

The frictions in the model include real ones of paid-in-advance intermediate inputs and costly capital adjustments and financial ones of costly equity and debt issuances. How much does each friction account for the measured misallocation in the calibrated model? More importantly, do intermediate input frictions help to account for more of the misallocation in the ASIF data, in addition to that generated by capital frictions in a standard investment model?

To answer these questions, we implement several counterfactual experiments that remove subsets of the frictions. Our purpose is to decompose a Hsieh and Klenow (2009)-type of static misallocation into different parts.

Experiments We introduce how we design our experiments as follows. *Exp 1* removes the financial friction on intermediate inputs. To do so, we modify the post-equity issuance dividend D as

$$d_{it} = \Pi_{it}(z_{it}, K_{it}, B_{it}) - (K_{it+1} - (1-\delta)K_{it}) - C(K_{it}, K_{it+1}) - b_{it} + q_{it}(z_{it}, B_{it+1}, K_{it+1}, M_{it+1})B_{it+1} \tag{36}$$

$$D_{it} = (1 + \mathbb{1}(d_{it} < 0)c_e)d_{it} - \frac{1}{1+r_1}\omega M_{it+1} \tag{37}$$

By this equation, firms finance intermediate inputs out of a separate zero-cost equity issuance (or equivalently, debt financing without enforcement frictions). Similarly, *Exp 2* removes the financial friction on capital with the modified D being

$$d_{it} = \Pi_{it}(z_{it}, K_{it}, B_{it}) - \frac{1}{1+r_1}\omega M_{it+1} - b_{it} + q_{it}(z_{it}, B_{it+1}, K_{it+1}, M_{it+1})B_{it+1} \tag{38}$$

$$D_{it} = (1 + \mathbb{1}(d_{it} < 0)c_e)d_{it} - (K_{it+1} - (1-\delta)K_{it}) - C(K_{it}, K_{it+1}) \tag{39}$$

Since we embed borrowing constraints on intermediate inputs through pay-in-advance, it is infeasible to remove the pay-in-advance friction alone. *Exp 3* thus removes the financial friction and the pay-in-advance friction on intermediate inputs together. Similarly, *Exp 4* removes capital adjustment costs and financial frictions on capital together. In these experiments, equity and debt issuances are still costly.[22] Lastly, *Exp 5* removes the four frictions on intermediate inputs and capital together by modifying d_{it} and D_{it} as in equation (38), letting intermediate inputs be flexible and setting $C(K_{it}, K_{it+1}) = 0$.

In this partial equilibrium framework, levels of output after the reallocation are not comparable across experiments. Thus, we quantify the potential gross-output and value-added gains among simulated firms from each experiment that are regenerated using calibrated parameters. The idea is to see how much the static misallocation would be if firms hypothetically lived in the counterfactual economy.

Results Table 8 presents the experiment results. Comparison between Benchmark and Exp 5 implies that one-period time-to-build capital friction combined with stochastic productivities drives the most gross-output and value-added losses, about 73% of the Benchmark model. The number is unexpectedly high given the

[22]The removal of financial frictions of one input is not equivalent to setting its recovery rate to 1, since the change of the recovery rate influences the debt financing for the other input.

rich specification of frictions in the model. However, this result is generally consistent with Asker et al. (2014), which find that the dynamic nature of capital, rather than the level of adjustment costs, accounts most for the cross-country misallocation differences.

If we compute the misallocation caused by each friction, Table 8 suggests a greater importance of financial frictions on intermediate inputs than that on capital. Differencing the Benchmark and Exp 1 implies that a 4.78% of the gross-output loss is attributed to financial frictions on intermediate inputs. The corresponding value-added loss is 12.35%. These numbers compare to 0.42% of the gross-output loss and 1.19% of the value-added loss from financial frictions on capital. This discussion contributes to existing studies which finds that the amount of misallocation from financially constrained capital could be small, if firms can self-finance (e.g., Midrigan and Xu, 2014; Moll, 2014). Our results show that if there are also financially constrained intermediate inputs, the importance of financial frictions would substantially increase.

When we include the misallocation induced by real frictions, Table 8 suggests that the relative quantitative importance of intermediate input frictions is not changed. Among the gross-output loss of 6.44% induced by intermediate input frictions, 26% is from pay-in-advance and 74% ((26.76-21.98)/(26.76-20.32)) is from financial frictions. Among a smaller gross-output loss of 2.61% induced by capital frictions (i.e., excluding the time-to-build on capital), 84% is from adjustment costs and 16% ((26.76 - 26.34)/(26.76-24.15)) from financial frictions. Compared to the gross-output loss in the ASIF data, we conclude that intermediate input frictions account for 17% of the misallocation in China, while capital frictions account for 6.8%.

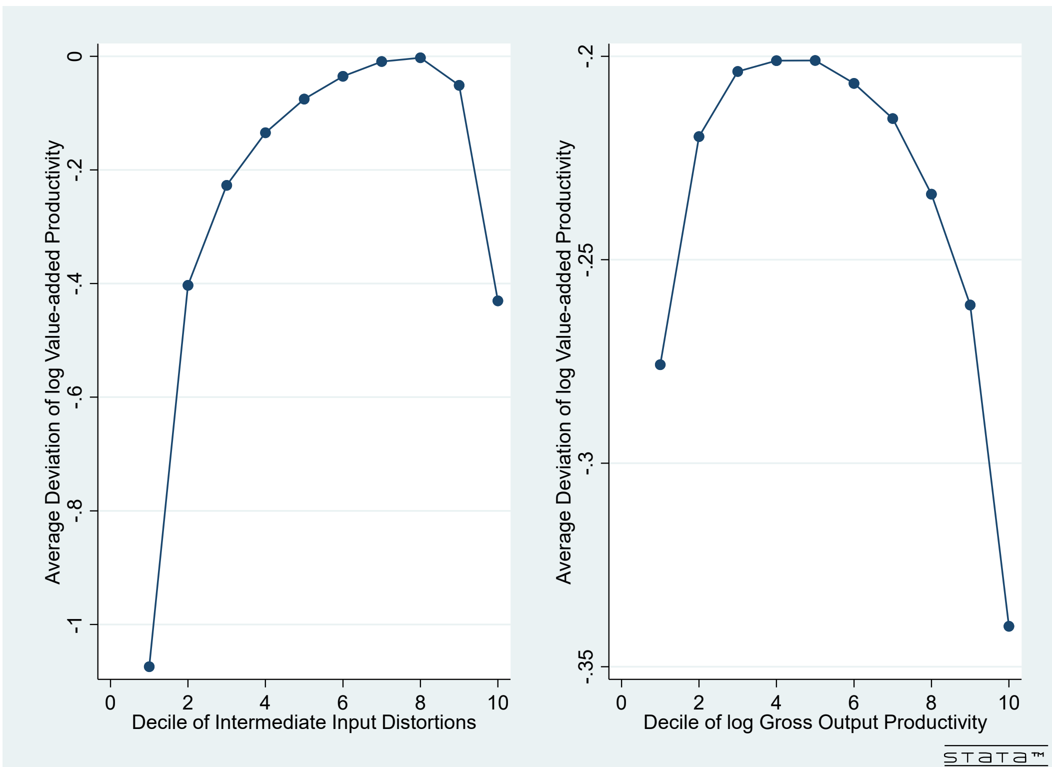
If we further expand the sample to all simulated firms instead (i.e., the hypothetical set of all manufacturing firms in China), the magnitudes of potential gross-output and value-added gains from removing four frictions are larger in the first row of Table 8. This result is driven by more smaller and constrained firms in the bottom 80% of the size distribution. Qualitatively and quantitatively, the relative importance of different frictions on intermediate inputs and capital in accounting for the misallocation is similar among all simulated firms.

5 Conclusion

The conventional Hsieh and Klenow (2009) approach models firms as value-added producers and reallocates capital and labor according to measured value-added quantity productivities. This paper shows that size-dependent intermediate input distortions could induce an underestimated measure of misallocation under this conventional approach. The reason is tha value-added productivities contain distortions and are biased downwards disproportionately for most productive firms. We provide direct evidence of two intermediate input frictions in the Chinese ASIF data: pay-in-advance and financial frictions. Quantitative analysis shows that intermediate input frictions, primarily the size-dependent financial friction, account for an important amount of misallocation in the Chinese data.

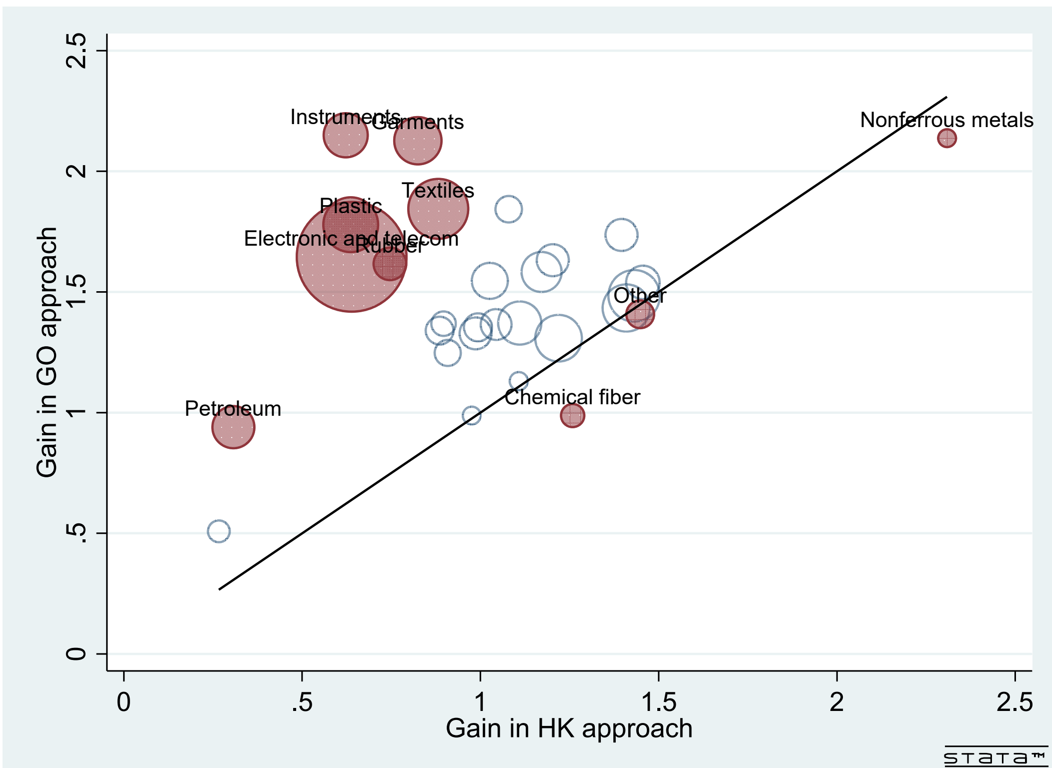
We contribute to the literature by emphasizing the importance of the size-dependent nature of intermediate input distortions when comparing the magnitude of misallocation under two alternative lenses: one using the value-added output and the other using the gross output. We also contribute by specifying the names of intermediate input frictions. One caveat of this paper is in its partial equilibrium framework without the input-output linkage and amplification (Acemoglu et al., 2012; Bartelme and Gorodnichenko, 2015; Liu, 2019; Osotimehin and Popov, 2020). Nevertheless, the paper provides a first-order investigation of the empirical and quantitative effect of intermediate input frictions.

Figure 1: Downward Biases of Value-added Productivities across Deciles of τ_{is}^m and $logA_{is}$



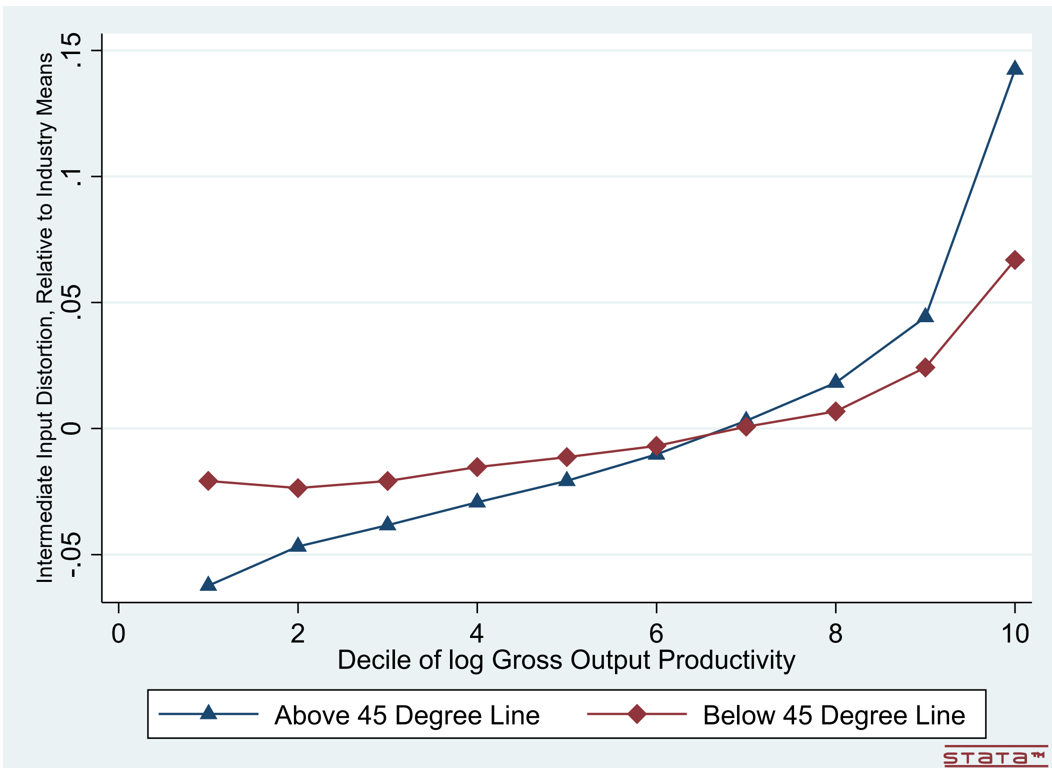
Notes: The top and bottom 1% of the gross-output TFPR and TFPQ distributions are trimmed. The bias is defined as $logA_{is}^{v}(\tau^{m}) - logA_{is}^{v}(0)$. Deciles of intermediate input distortions and log gross output productivity are calculated for the pooled 1998 - 2007 data.

Figure 2: Industry-level Value-added Gains under the HK and the GO Approaches, 2004



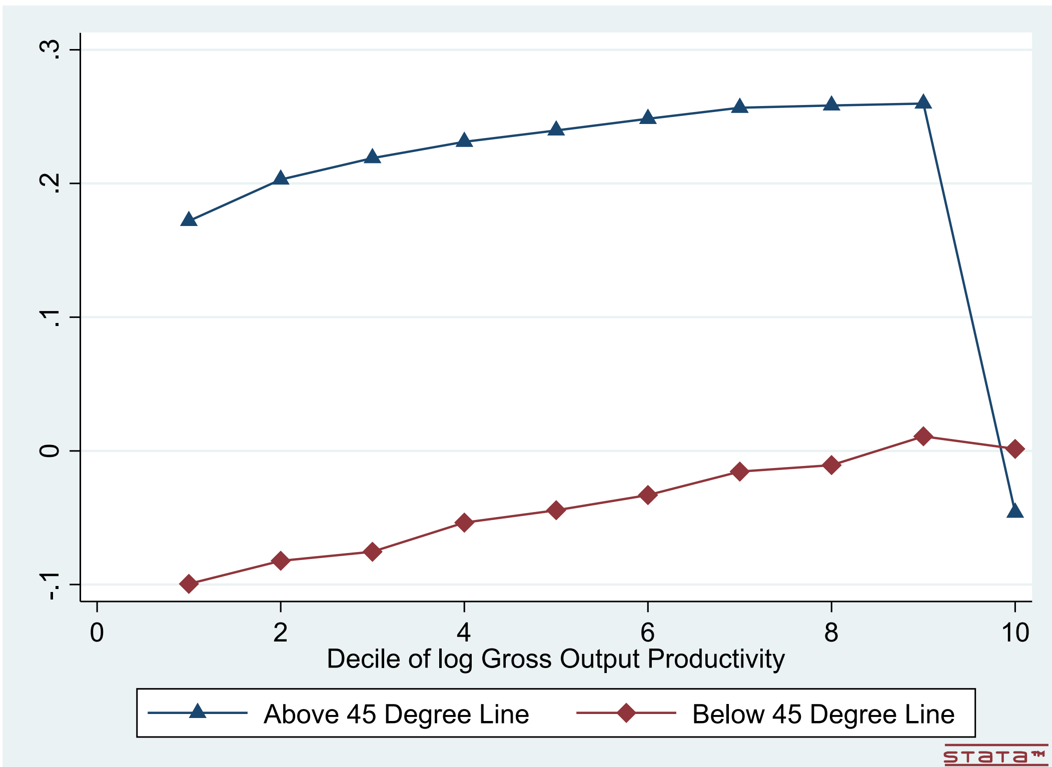
Notes: X-axis and Y-axis represent for value-added gains under the HK and the GO approaches, respectively. Sizes of circles are proportional to the industry-level value-added revenues.

Figure 3: Average Deviations of τ_{is}^{m} from Industry-Means across Deciles of $logA_{is}$



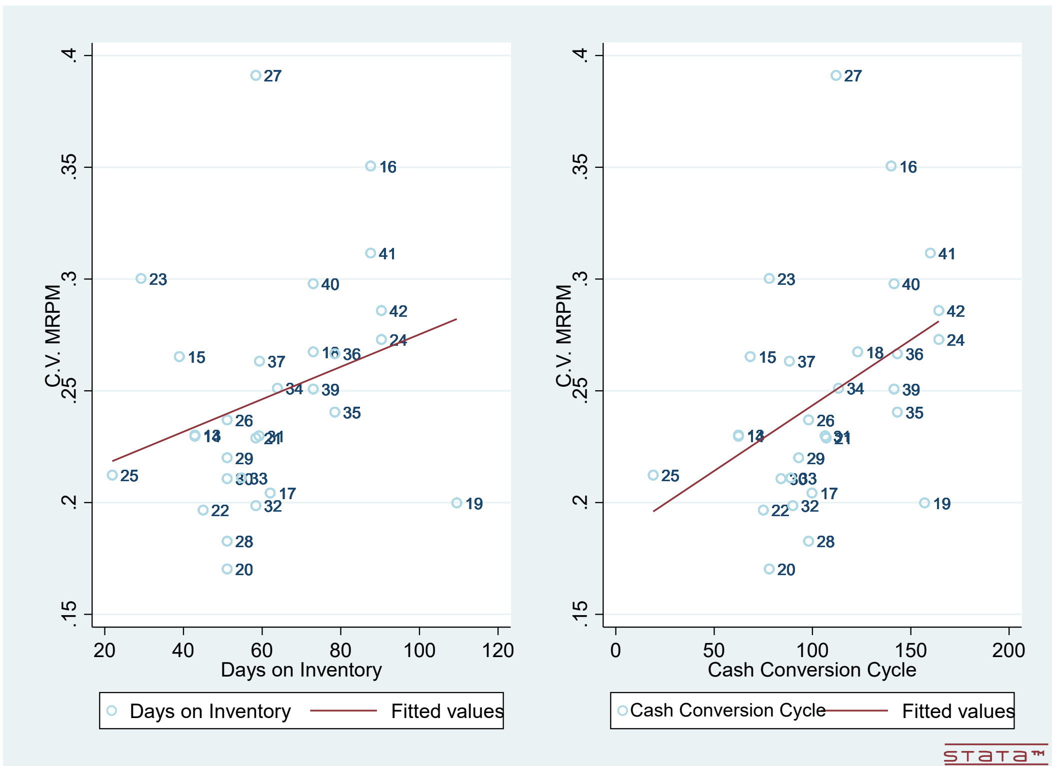
Notes: For each decile of productivities in the above and below groups, deviations of τ_{is}^{m} are calculated as the difference between τ_{is}^{m} and its industry-level average. The "above 45 degree line" group are industry-year observations that lie above the 45 degree line in Figure 2. Vice versa for the "below 45 degree line" group. Deciles of log gross output productivity are calculated within industries.

Figure 4: Average Differences of $(K_{is}^{eff,\nu} - K_{is}^{eff})/K_{is}^{eff}$ across Deciles of $log A_{is}$



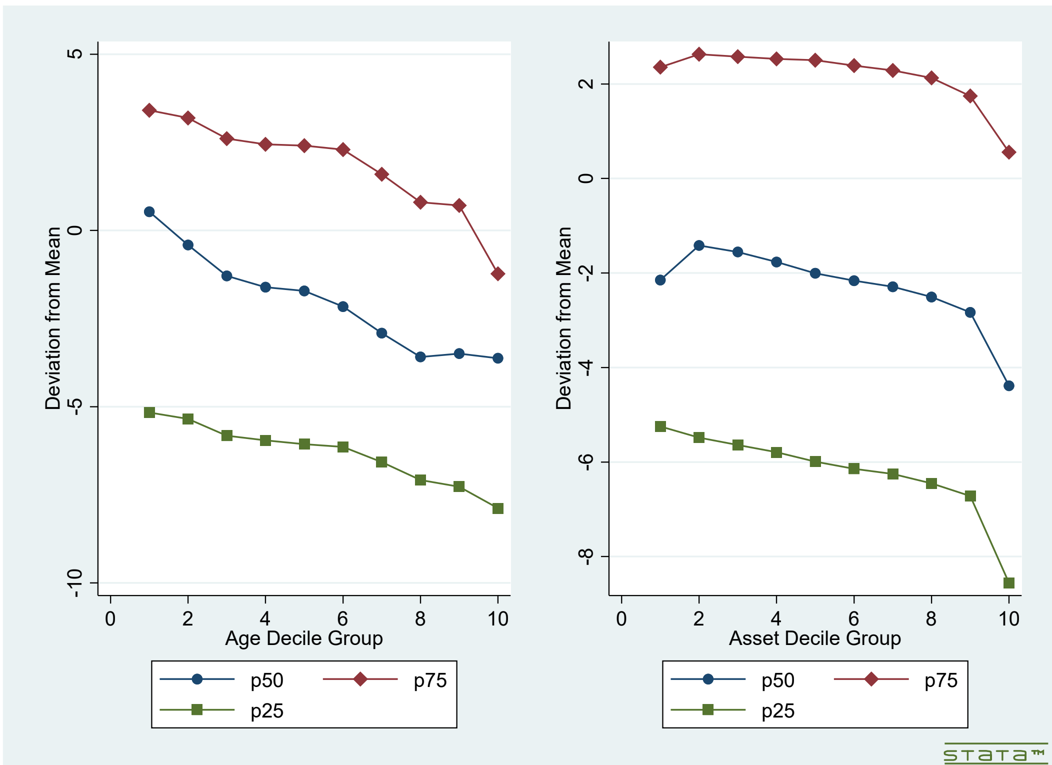
Notes: $K_{is}^{eff,\nu}$ is the level of post-reallocation "efficient" capital under the HK approach and K_{is}^{eff} is the level under the GO approach. The "above 45 degree line" group are industry-year observations that lie above the 45 degree line in Figure 2. Vice versa for the "below 45 degree line" group. Deciles of log gross output productivity are calculated within industries.

Figure 5: Intermediate Input Misallocation and the Length of Pay-in-Advance



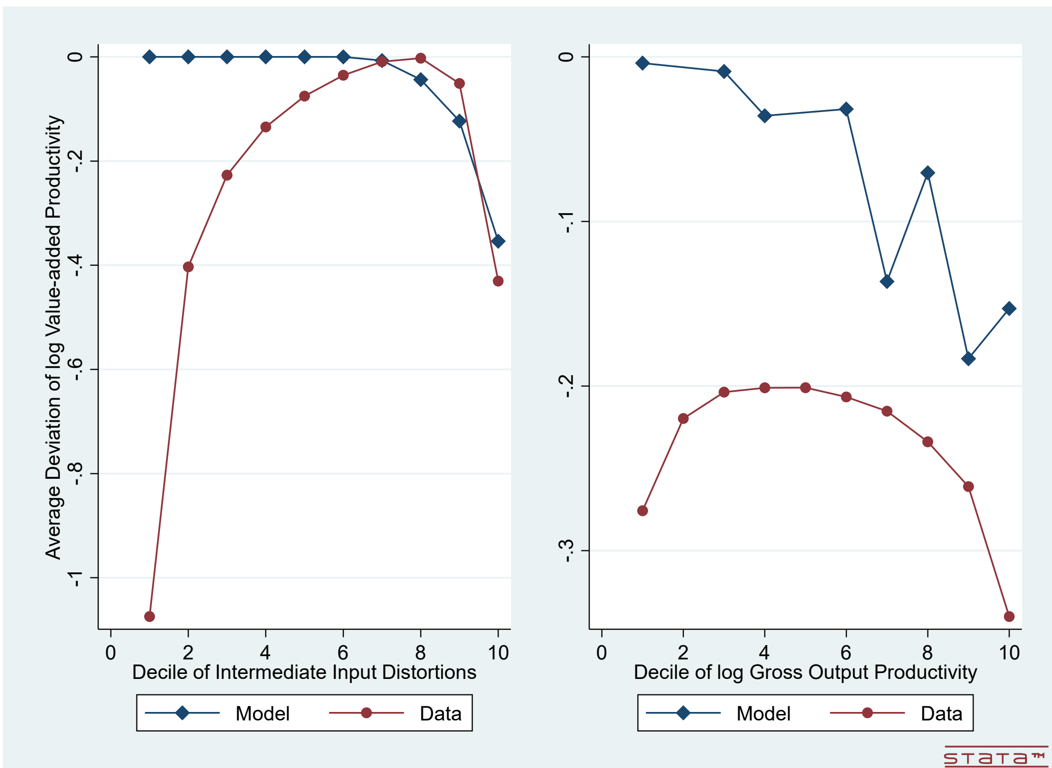
Note: $CV(MRPM_s)$ is the coefficient of variation for $logMRPM_{is}$ within industry s at year t and then averaged across years. The red line is the ordinary-least-square (OLS) fit across industries. The 2-digit labels are industry codes. The cash conversion cycle and days on inventory are from Raddatz (2003) and are converted to numbers of days as in equations (13) and (14).

Figure 6: 25th, 50th, and 75th Percentiles of Marginal Returns of Intermediate Inputs over Age and Asset Deciles, Pooled Data from 1998 to 2007



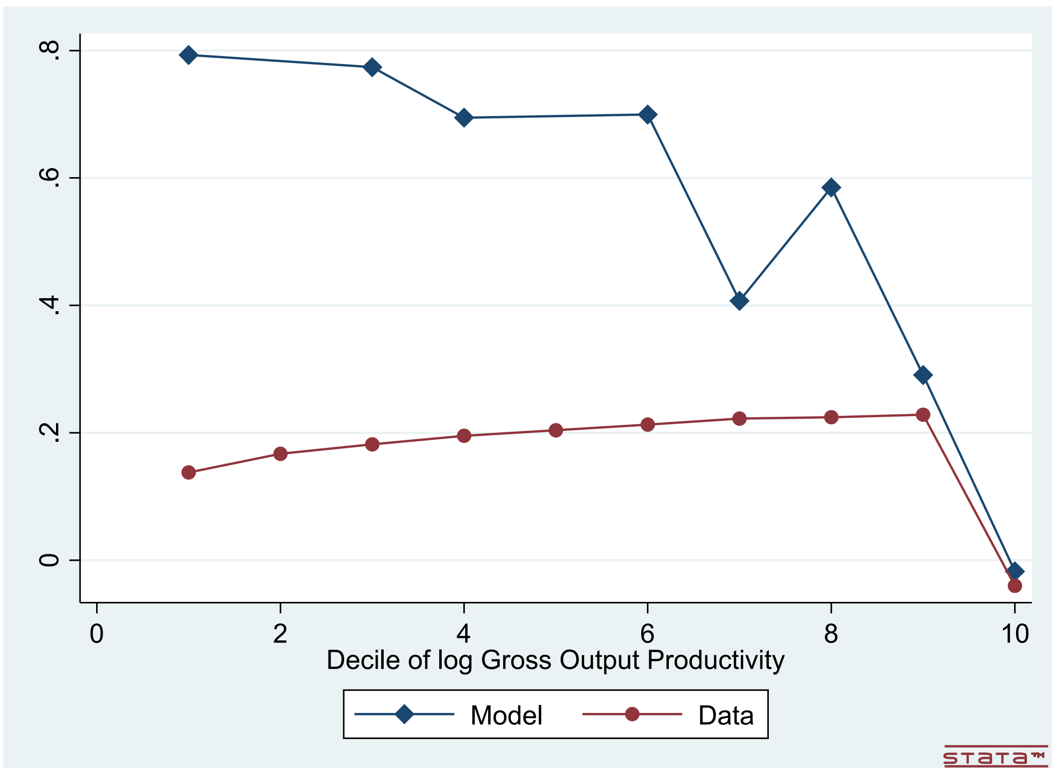
Notes: For each age or asset decile, the y-axis plots the 25th, 50th, and 75th percentiles of the distribution of residuals obtained from regressing $logMRPM$ on SOE, exporter dummies, and year and industry FEs in the pooled data from 1998 to 2007.

Figure 7: Downward Biases of Value-added Productivities across Deciles of τ_i^m and $logA_i$



Notes: The bias is defined as $logA_{is}^{v}(\tau^m) - logA_{is}^{v}(0)$. Deciles of intermediate input distortions and log gross output productivities are calculated for the pooled 1998 - 2007 data. Deciles in the model are calculated for the representative industry.

Figure 8: Average Differences of Capital $(K_i^{eff,\nu} - K_i^{eff})/K_i^{eff}$ across Deciles of $log A_i$



Notes: $K_{is}^{eff,\nu}$ is the level of post-reallocation "efficient" capital under the HK approach and K_{is}^{eff} is the level under the GO approach. Deciles of log gross output productivity are calculated within industries in the ASIF data and within the representative industry in the model simulation.

Table 1: Pay-in-advance Measures in China and the U.S. (Days)

	DI	CCC
China ASIF	44	50
China Listed	84	116
U.S. Compustat	62	107

Notes: U.S. numbers are from Raddatz (2003). For ASIF firms, the DI comes from the pooled 1998-2007 data, while the CCC is from the pooled 2004-2007 data since account payables are absent before 2004. Data for listed Chinese firms are from China Stock Market & Accounting Research (CSMAR). Similar to Raddatz (2003), both DI and CCC are first the medians at the industry level and then averaged across industries. We trim the top and bottom 1% of each statistic in the Chinese data.

Table 2: Effects of Provincial Financial Development on Intermediate Input Misallocation for Industries with Different Financial Vulnerabilities

	FinDevp = LoanMkt			FinDevp = DepMkt		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg MRPM	0.3161***	0.3204***	0.3217***	0.3138***	0.3171***	0.3185***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
CV MRPK			0.0077**			0.0084**
			(0.00)			(0.00)
FinDevp	-0.0054*	-0.0068*	-0.0066*	-0.0025	-0.0019	-0.0020
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FinDevp*AssetTang	0.0159***	0.0206***	0.0202***	0.0065**	0.0066**	0.0065**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
FinDevp*ExtFin	-0.0008	-0.0026	-0.0027	-0.0005	-0.0032	-0.0033
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FinDevp*DIHi	0.0036***	-0.0055	-0.0055	0.0042***	-0.0039	-0.0046
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FinDevp*NTCHi	0.0044***	0.0184***	0.0180***	0.0034**	0.0136**	0.0140**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FinDevp*AssetTang*DIHi		0.0459**	0.0463***		0.0565**	0.0596***
		(0.01)	(0.01)		(0.02)	(0.02)
FinDevp*ExtFin*DIHi		-0.0196**	-0.0195**		-0.0303***	-0.0307***
		(0.01)	(0.01)		(0.01)	(0.01)
FinDevp*AssetTang*NTCHi		-0.0754***	-0.0742***		-0.0753***	-0.0769***
		(0.02)	(0.02)		(0.02)	(0.02)
FinDevp*ExtFin*NTCHi		0.0241***	0.0241***		0.0347***	0.0352***
		(0.01)	(0.01)		(0.01)	(0.01)
SOE Share	0.0429***	0.0399***	0.0387**	0.0454***	0.0413***	0.0398**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Exporter Share	0.0198	0.0202	0.0186	0.0175	0.0163	0.0144
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.1563***	-0.1813***	-0.1943***	-0.0489	-0.1272***	-0.1423***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7362	7362	7362	7362	7362	7362
adj. R-sq	0.495	0.497	0.498	0.494	0.495	0.497
Standard errors in parentheses						
=”* p<0.05	** p<0.01	*** p<0.001”				

Notes: The top and bottom 1% of $logMRPM$ and $logMRPK$ are trimmed. Observations are at the industry-province-year level. $DIHi$ and $NTCHi$ are dummy variables that equal to 1 if industries have DI and NTC higher that the cross-industry average and 0 otherwise, respectively.

Table 3: Model Parametrization

Parametrized			**Calibrated**		
Parameter		Value	Parameter		Value
Discounting factor	β	0.94	Return to scale	η	0.85
Depreciation rate	δ	0.09	Labor share	$\tilde{\beta}_l$	0.5
Capital adjustment cost			Intermediate input share	$\tilde{\beta}_m$	0.61
Fixed cost	ξ	0.039	Fraction of intermediate inputs in advance	ω	40%
Convex cost	θ	0.049	Threshold sales	y_c	23.24
Interest rates			Exit rate	ψ	0.08
Saving rate	r_1	0.03	*Recovery rates*		
Risk-free borrowing rate	r_2	0.06	Capital	γ_1	0.60
Equity issuance cost	c_e	0.30	Intermediate inputs	γ_2	0.10
			Transitory productivity		
			Persistence	ρ	0.80
			Standard deviation	σ_ϵ	0.24
			Permanent productivity		
			Mean	$\mu_{\bar{z}}$	0.90
			Standard deviation	$\sigma_{\bar{z}}$	0.30
			Initial wealth distribution of entrants		
			Mass of entrants	μ_{ent}	0.17
			Pareto shape	α	50.00
			Minimum wealth	a_{min}	8.00

Table 4: Model Moments Compared to Data

Moments	Data	Model
Targeted		
All firms		
Market share by firms of top 10% sales	97.34%	87.50%
Exit rate	8.00%	8.00%
Frac. of firms above threshold	20.00%	20.00%
Top 20%		
Leverage	0.56	0.54
Leverage(%)-asset slope	0.07	0.07
Corr(productivity z, productivity lag 1 z_{-1})	0.61	0.65
Average productivity z	1.98	1.88
SD(productivity z)	0.43	0.37
5-year unbalanced & top 20%		
Corr(productivity z, productivity lag 5 z_{-5})	0.39	0.23
Fraction of newly-established firms above threshold sales	6.94%	7.56%
Relative size of newly-established firms	65.56%	96.50%
Fraction of incumbents in end-year entrants	37.09%	40.04%
Not Targeted		
Top 20%		
Intm-output-ratio-(%)-asset slope	0.12	0.06
Capital-output-ratio(%) -asset slope	3.32	1.43
S.D. interest rate	0.03	0.14
C.V.($MRPM$)	0.33	0.20
C.V.($MRPK$)	1.67	0.95

Notes: Leverage is computed as debt over the asset. In the model, asset corresponds to the sum of capital and pre-paid intermediate inputs. The leverage(%)-asset slope is obtained by regressing the leverage ratio (%) on the asset percentiles. Intm-output-ratio(%)-asset slope and capital-output-ratio(%)-asset slope are similarly defined. Over a 5-year window, newly-established firms are the ones with ages younger than five by the end year. End-year entrants are firms that are not in the ASIF at the beginning of the 5-year window, but show up by the end year. There firms could be newly-established ones or the ones that expand with their sales surpassing the threshold level during the 5-year window.

Table 5: Comparative Statics when Varying c_e, γ_1 and γ_2

	Benchmark	c_e		γ_1		γ_2	
		0	1	0	1	0	1
Frac. issue equity	74.30%	80.2%	73.35%	72.16%	77.50%	74.06%	82.22%
Frac. default	0.01%	0.01%	0.04%	0	0.13%	0	0.05%
Avg. lev. ratio	0.54	0.57	0.36	0.45	0.58	0.48	0.64
Leverage(%)-asset slope	0.07	-0.08	4.24	-0.16	0.35	0.06	0.24
Avg. capital	576.6	874.61	360.92	459.63	674.08	562.37	621.59
Avg. *MRPM*	1.11	1.07	1.15	1.10	1.13	1.11	1.11
Sd. *MRPM*	0.22	0.15	0.25	0.19	0.27	0.21	0.21
Avg. *MRPK*	0.41	0.37	0.83	0.50	0.36	0.42	0.37
Sd. *MRPK*	0.39	0.36	0.72	0.46	0.37	0.41	0.38

Notes: Statistics are for the top 20% firms in the sales distribution. Leverage(%)-asset slope is obtained by regressing the leverage ratio (%) on the asset percentiles.

Table 6: Size-dependent Distortions: Model vs ASIF

	ASIF Data	Model Simulated Data
$corr(\tau^m, logA)$	0.27	0.49
$corr(\tau^k, logA)$	0.58	0.56
$corr(\tau^k, \tau^m)$	-0.01	0.19
$sd(logA)$	0.43	0.37
$sd(logTFPR)$	0.32	0.17
$sd(logA^v)$	1.45	0.90
$sd(logTFPR^v)$	0.65	0.34

Notes: $logTFPR(logTFPR^v)$ is the revenue productivity using the gross-output (value-added) production function.

Table 7: Output Gains via Reallocations: Model vs ASIF

Input(s) Reallocated	Gross Output	Value Added
Top 20%, Model		
M	3.40%	8.88%
K,L	8.60%	22.13%
K,L,M	26.76%	68.62%
All Firms, Model		
M	3.48%	8.92%
K,L	9.93%	25.40%
K,L,M	28.35%	72.67%
ASIF Data		
M	3.24%	12.72%
K,L	11.36%	46.15%
K,L,M	37.88%	159.07%

Notes: In the ASIF data, the top and bottom 1% of TFPR and TFPQ distributions are trimmed. Gross-output and value-added gains are first calculated for each year and then averaged.

Table 8: Simulated Gains by Equalizing Marginal Products, Benchmark and Counterfactuals

	Top 20% Firms		All Firms	
	Gross Output	Value Added	Gross Output	Value Added
Data	37.88%	159.07%	-	-
Model				
Benchmark	26.76%	68.62%	28.34%	72.67%
Exp 1 (no fin. frictions on M)	21.98%	56.27%	22.30%	57.18%
Exp 2 (no fin. frictions on K)	26.34%	67.43%	27.79%	71.23%
Exp 3 (no frictions on M)	20.32%	52.02%	20.63%	52.90%
Exp 4 (no frictions on K)	24.15%	61.82%	24.89%	63.82%
Exp 5 (no frictions on M and K)	19.43%	49.81%	19.73%	50.59%

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Appendix

Matching Firms across Years The original ASIF data is cross-sectional and requires matching of firms over time to understand the dynamics. We match firms across years based on codes in Brandt et al. (2012) with some modifications. Firms are matched sequentially according to their registration IDs, names, a string that combines names of legal representatives, industry and area codes, a string that combines phone numbers, industry and area codes, and lastly a string that combines opening year, geographic code, industry, township/streets/villages and product names. Entry and exit rates in the merged data are plotted in Figure A1 in comparison to Brandt et al. (2012). One can see that matching results are close. Note that entries and exits in the ASIF data are not equivalent to those in the model. We also use the same perpetual inventory method from their paper to construct the firm-level real capital stock over time.

One-Input Reallocation This appendix introduces how Section 4 calculates gross-output and value-added gains by reallocating one input at a time. To simplify the notation, we use $\tilde{\alpha}_k^s$, $\tilde{\alpha}_l^s$, and $\tilde{\alpha}_m^s$ to represent $\beta_k^s(1-\beta_m^s)$, $(1-\beta_k^s)(1-\beta_m^s)$, and β_m^s in the paper. Note the industry-level $T\bar{FPR}_s$

$$T\bar{FPR}_s = \frac{P_s Y_s}{K_s^{\tilde{\alpha}_k^s} L_s^{\tilde{\alpha}_l^s} M_s^{\tilde{\alpha}_m^s}} = \frac{\sum_{i=1}^{N_s} P_{is} Y_{is}}{K_s^{\tilde{\alpha}_k^s} L_s^{\tilde{\alpha}_l^s} M_s^{\tilde{\alpha}_m^s}} \tag{40}$$

and hence the industry-level productivity

$$\begin{aligned}
TFP_s =& \frac{Y_s}{K_s^{\tilde{\alpha}_k^s} L_s^{\tilde{\alpha}_l^s} M_s^{\tilde{\alpha}_m^s}} = T\bar{FPR}_s / P_s \\
=& T\bar{FPR}_s \left(\sum_{i=1}^{N_s} \left(\frac{A_{is}}{TFPR_{is}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \\
=& \left(\sum_{i=1}^{N_s} \left(A_{is} \frac{T\bar{FPR}_s}{TFPR_{is}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \\
=& \left(\sum_{i=1}^{N_s} \left(A_{is} \frac{M\bar{RPK}_s^{\tilde{\alpha}_k^s} M\bar{RPM}_s^{\tilde{\alpha}_m^s} M\bar{RPL}_s^{\tilde{\alpha}_l^s}}{MRPK_{is}^{\tilde{\alpha}_k^s} MRPM_{is}^{\tilde{\alpha}_m^s} MRPL_{is}^{\tilde{\alpha}_l^s}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}
\end{aligned} \tag{41}$$

Note that $A_{is} = \frac{R_{is}^{\frac{\sigma}{\sigma-1}}}{K_{is}^{\tilde{\alpha}_k^s} L_{is}^{\tilde{\alpha}_l^s} M_{is}^{\tilde{\alpha}_m^s}} (P_s^{\sigma} Y_s)^{-\frac{1}{\sigma-1}}$, where R_{is} is firm-level gross-output revenue in the data. According to Equation (41), industry TFP_s in the data could be computed with a multiplier $(P_s^{\sigma} Y_s)^{-\frac{1}{\sigma-1}}$.

If only intermediate inputs are reallocated to equalize its marginal revenue products within industries, $M\bar{R}PM_s = MRPM_{is}$ holds after the reallocation. The reallocation, however, changes the firm-level gross-output revenue

$$R'_{is} = (P_{is} Y_{is})' = A_{is} K_{is}^{\tilde{\alpha}_k^s} L_{is}^{\tilde{\alpha}_l^s} M_{is}^{'\tilde{\alpha}_m^s} (Y'_s P_s^{'\sigma})^{\frac{1}{\sigma}} \tag{42}$$

where R'_{is} or $(P_{is} Y_{is})'$, M'_{is}, Y'_s, and P'_s denote revenue, intermediate inputs, industry-level output quantity, and industry-level price after the reallocation. Firm-level and industry-level marginal revenue products of capital and labor also change accordingly. The co-movement of industry- and firm-level marginal products helps to cancel out $(Y'_s P_s^{'\sigma})^{\frac{1}{\sigma}}$ in equation (41) after the reallocation. The new industry TFP'_s is

$$TFP'_s = (\sum_{i=1}^{N_s} (A_{is} \frac{M\bar{R}PK_s^{'\tilde{\alpha}_k^s} M\bar{R}PL_s^{'\tilde{\alpha}_l^s}}{MRPK_{is}^{'\tilde{\alpha}_k^s} MRPL_{is}^{'\tilde{\alpha}_l^s}})^{\sigma-1})^{\frac{1}{\sigma-1}} \tag{43}$$

where $MRPX'$ is the new marginal product, $x = K, L$. Thus, gross-output gain for industry s is

$$log(TFP'_s / TFP_s) \tag{44}$$

which cancels out $(P_s^{\sigma} Y_s)^{-\frac{1}{\sigma-1}}$ in both A_{is}s in the numerator and the denominator. The economy-wide gross-output gain is an industry gross-output weighted gain

$$\sum_{s=1}^{S} \theta_s log(TFP'_s / TFP_s) \tag{45}$$

Gross-output gains from reallocating capital or labor are computed similarly. Following Hang et al. (2020), the value-added gain is

$$\frac{1}{1 - \tilde{\alpha}_m^s} \sum_{s=1}^{S} \theta_s log(TFP'_s / TFP_s) \tag{46}$$

The two-input and three-input reallocations could be similarly calculated.

Financially Vulnerable Measures and Provincial Financial Market Indices Table A1 lists asset tangibility and external finance dependence measures for 28 2-digit industries. Table A2 and A3 reports the provincial financial market development indices. Table A4 use these indices and replicate results in Table 3 using the continuous CCC and NTC. Table A5 investigates whether results for Table 3 hold for capital.

The ASIF Data and Census 2004 The ASIF data 1998-2007 has a threshold sales of 5 million yuan. Table A6 describes the differences between the ASIF data and the Economic Census 2004. One can see that ASIF firms are the largest 20% of all manufacturing firms in the Census. Average sales, capital, and employment in the ASIF data are almost six times as large as those in the Census data. Firms in the Census are also younger on average. Nevertheless, the ASIF data produces about 90% of manufacturing output and employs 70% of workers.

Proof of Value-added Productivity Using the gross-output production function, the first order condition of intermediate inputs is

$$P_s Y_s^{\frac{1}{\sigma}} A_{is}^{\frac{\sigma-1}{\sigma}} \beta_m^s \frac{\sigma-1}{\sigma} M_{is}^{\frac{\sigma-1}{\sigma}\beta_m^s - 1} (K_{isk}^{\beta_s} L_{is}^{1-\beta_k^s})^{(1-\beta_m^s)\frac{\sigma-1}{\sigma}} = P_m(1+\tau_{is}^M) \tag{47}$$

Therefore the value-added revenue is

$$\begin{aligned} P_{is}^v Y_{is}^v &:= P_{is} Y_{is} - P_m M_{is} = [1 - \frac{\beta_m^s(\sigma-1)}{\sigma(1+\tau_{is}^m)}] P_{is} Y_{is} \\ &= [1 - \frac{\tilde{\beta}_m^s}{1+\tau_{is}^m}](P_s Y_s^{\frac{1}{\sigma}})^{\frac{1}{1-\tilde{\beta}_m^s}} [\frac{\tilde{\beta}_m^s}{(1+\tau_{is}^m) P_m}]^{\frac{\tilde{\beta}_m^s}{1-\tilde{\beta}_m^s}} (A_{is}^{\alpha_a^s})^{\frac{\sigma-1}{\sigma}} (K_{is}^{\alpha_k^s} L_{is}^{\alpha_l^s})^{\frac{\sigma-1}{\sigma}} \end{aligned} \tag{48}$$

where $\alpha_a^s = \frac{1}{1-\tilde{\beta}_m}$, $\alpha_k^s = \frac{\beta_k^s(1-\beta_m^s)}{1-\tilde{\beta}_m^s}$, and $\alpha_l^s = \frac{\beta_l^s(1-\beta_m^s)}{1-\tilde{\beta}_m^s}$. The second equation holds by expressing M_{is} as a function of K_{is} and L_{is} from equation (47).

Since $Y_{is}^v = (\frac{P_{is}^v Y_{is}^v}{P_s^v (Y_s^v)^{\frac{1}{\sigma}}})^{\frac{\sigma}{\sigma-1}}$, we obtain the value-added productivity as expressed in the main text.

Proof of Proposition 1

(1) Let $\tilde{\tau}_{is}^m = \frac{1}{1+\tau_{is}^m}$:

$$\frac{\partial \chi_{is}}{\partial \tilde{\tau}_{is}^m} = P_m^{\frac{\tilde{\beta}_m^s}{1-\tilde{\beta}_m^s}} \frac{\tilde{\beta}_m^s}{1-\tilde{\beta}_m^s} (\tilde{\tau}_{is}^m)^{\frac{\tilde{\beta}_m}{1-\tilde{\beta}_m}} [(\tilde{\tau}_{is}^m)^{-1} - 1] \tag{49}$$

which is negative if $\tilde{\tau}_{is}^m$ >1 (i.e., $\tau_{is}^m < 0$) and positive if $\tilde{\tau}_{is}^m$ <1 (i.e., $\tau_{is}^m > 0$). Since $\tilde{\tau}_{is}^m$ is decreasing in τ_{is}^m, χ_{is}^m is decreasing in τ_{is}^m for positive τ_{is}^m, increasing for negative τ_{is}^m. The second order derivative shows the maximum is obtained when $\tau_{is}^m = 0$.

(2) when $corr(\tau_{is}^m, logA_{is}) \neq 0$, one can rewrite

$$\tau_{is}^m = c_0 + \rho logA_{is} + \zeta_{is} \tag{50}$$

where c_0 is a constant, $\rho \neq 0$, and $E(\zeta_{is}) = 0$.

The deviation of log value-added quantity productivity:

$$\begin{aligned}
\frac{\sigma-1}{\sigma}\Delta logA_{is}^v &= log\chi_{is}(\tau_{is}^m) - log(\chi_{is}(0)) \\
&= -\frac{\tilde{\beta}_m^s}{1-\tilde{\beta}_m^s} log(1+\tau_{is}^m) + log(1 - \frac{\tilde{\beta}_m^s}{1+\tau_{is}^m}) - log(1-\tilde{\beta}_m^s) \\
&\approx -\frac{\tilde{\beta}_m^s}{1-\tilde{\beta}_m^s}(\tau_{is}^m - 0.5(\tau_{is}^m)^2) + \frac{1}{1-\tilde{\beta}_m^s}\tau_{is}^m - 0.5\frac{1}{(1-\tilde{\beta}_m^s)^2}(\tau_{is}^m)^2 \\
&= \tau_{is}^m + a(\tau_{is}^m)^2
\end{aligned} \tag{51}$$

where $a = 0.5\frac{\tilde{\beta}_m^s(1-\tilde{\beta}_m^s)-1}{(1-\tilde{\beta}_m^s)^2} < 0$. The approximate equation holds by Taylor expansions up to an order two. Therefore

$$\frac{\sigma-1}{\sigma} E(\Delta logA_{is}^v | A_{is}) = a\rho^2 logA_{is}^2 + \rho(1+2ac_0)logA_{is} + ac_0^2 + aVAR(\zeta_{is}) + c_0 \tag{52}$$

The parabola reaches the maximum at $logA_0 = -\frac{1+2ac_0}{2a\rho}$. Thus for $logA_{is} \in [logA_0, \infty)$, average deviation is decreasing in $logA_{is}$. Vice versa for $logA_{is} \in$

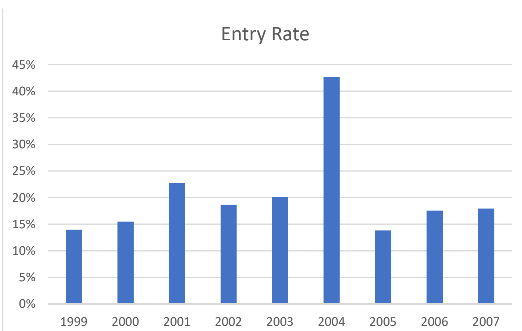
$(-\infty, logA_0)$. Meanwhile,

$$\frac{\partial \frac{\sigma-1}{\sigma} E(\Delta logA_{is}^{\nu}|A_{is})}{\partial \rho} = 2a\rho logA_{is}^2 + (1+2ac_0) \tag{53}$$

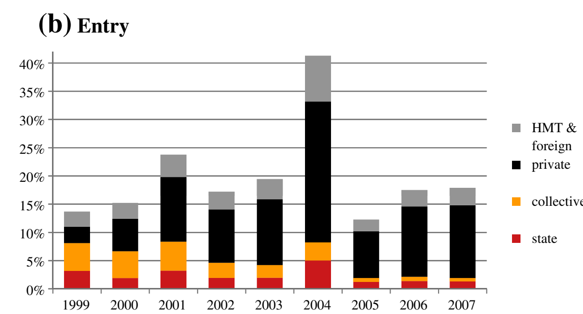
which is negative for sufficiently large $logA_{is}$ when distortions are size-dependent, i.e., $\rho > 0$. Therefore, more size-dependent distortions cause a disproportionately negative deviation of $logA_{is}^{\nu}$ for very productive firms.

Figure A1: Entry and Exit Rates in the ASIF Data, Compared to Brandt et al. (2012)

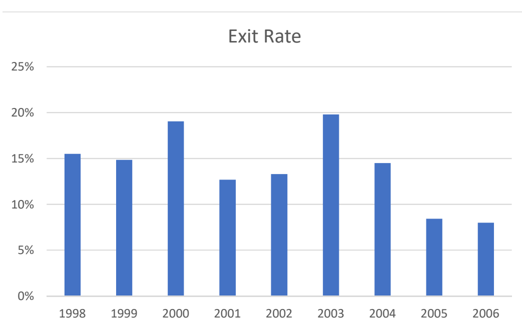
(a) Entry: This Paper



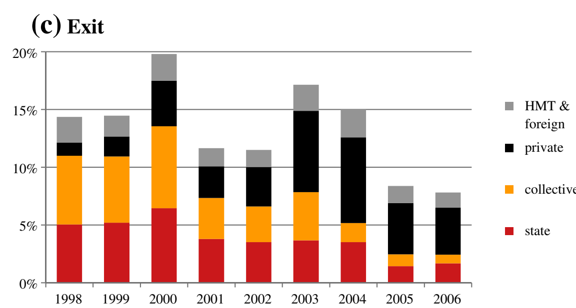
(b) Entry: Brandt et al. (2012)



(c) Exit: This Paper

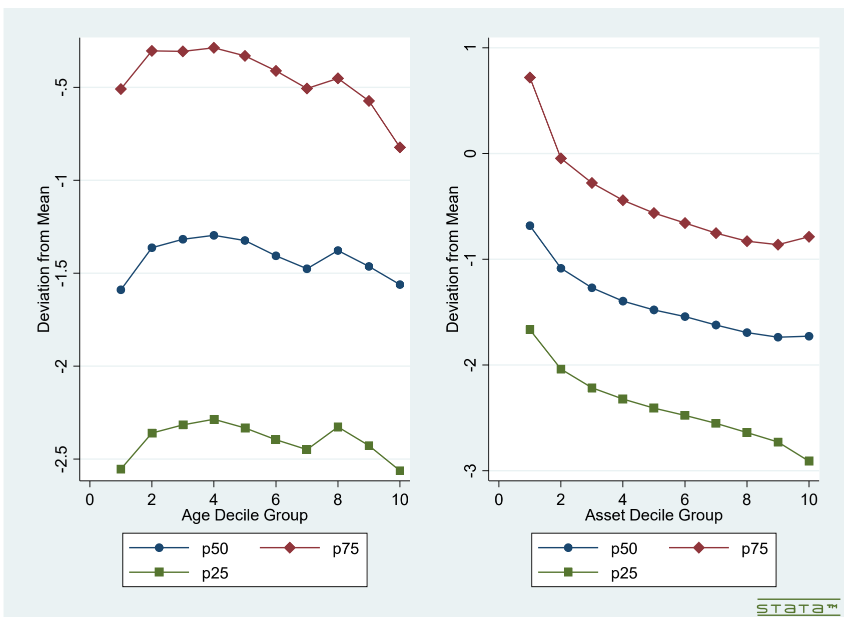


(d) Exit: Brandt et al. (2012)



Notes: Entrants (exits) include (1) firms enter into (exit from) production as in the model; (2) firms grow above (decline below) 5 million threshold sales.

Figure A2: Percentiles of Marginal Returns of Capital over Asset Deciles, 1998-2007



Notes: The *y*-axis plots the residual after regression $logMRPK$ on SOE, exporter dummies, year and industry year fixed effects in the pooled 1998-2007 data.

Table A1: Asset Tangibility, External Finance Dependence, DI and CCC Measures in 2-digit CIC Industries

Industry	Asset Tangibility	External Finance Dependence	DI	CCC
13 Food processing	0.38	0.14	42.89	62.38
14 Manufacture of foods	0.38	0.14	42.89	62.38
15 Manufacture of beverages	0.28	0.08	38.93	68.33
16 Manufacture of tobacco	0.22	0.45	87.60	140.00
17 Manufacture of textiles	0.37	0.40	62.05	99.75
18 Garments and other fiber products	0.13	0.03	73.00	123.00
19 Leather, furs, down and related products	0.09	0.14	109.50	157.00
20 Timber processing, bamboo,cane, palm fiber and straw products	0.38	0.28	51.10	78.00
21 Manufacture of furniture	0.26	0.24	58.40	107.00
22 Paper-making and paper products	0.56	0.18	45.02	75.00
23 Printing and recorded media	0.30	0.20	29.20	78.00
24 Cultural, educational and sports goods	0.19	0.47	90.34	164.25
25 Petroleum processing and coking	0.67	0.04	21.90	19.00
26 Raw chemical materials,and chemical products	0.32	0.52	51.10	98.00
27 Medical and pharmaceutical products	0.20	0.22	58.40	112.00
28 Chemical fiber	0.32	0.52	51.10	98.00
29 Rubber products	0.38	0.23	51.10	93.00
30 Plastic products	0.34	1.14	51.10	84.00
31 Nonmetal mineral products	0.28	0.25	59.21	106.44
32 Smelting and pressing of ferrous metals	0.46	0.09	58.40	90.00
33 Smelting and pressing of nonferrous metals	0.38	0.01	54.75	89.00
34 Metal products	0.28	0.24	63.88	113.25
35 Ordinary machinery	0.18	0.45	78.48	143.17
36 Special purpose equipment	0.18	0.45	78.48	143.17
37 Transport equipment	0.25	0.31	59.31	88.25
39 Electric equipment and machinery	0.21	0.77	73.00	141.50
40 Electronic and telecommunications equipment	0.21	0.77	73.00	141.50
41 Instruments, meters, cultural and office equipment	0.15	0.96	87.60	160.00
42 Other manufacturing	0.19	0.47	90.34	164.25

Notes: Asset tangibility and external dependence measures are from Table I in Braun (2003). DI and CCC are from Raddatz (2003).

Table A2: Financial Makret Development Indices across Provinces, 1997-2007, Part 1

Index *LoanMkt* Based on the Fraction of Loans Lent to Non-State Owned Enterprises											
Province	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Shanghai	2.72	3.03	1.93	1.91	8.08	8.88	9.76	9.7	9.78	9.92	9.97
Yunnan	0	0.28	0.33	1.6	3.34	3.83	5.39	7.61	8.41	10.07	10.05
Inner Mongolia	1.69	1.76	0.64	0.89	1.89	3.17	5.05	6.09	7.92	8.25	8.94
Beijing	4.69	4.3	1.06	3.07	4.98	5.97	5.84	6.25	5.38	6.73	6.99
Jilin	1.54	0.77	1.16	1.22	0.29	0.77	2.4	3.71	2.69	2.92	5.94
Sichuan	4.98	5.35	2.86	2.6	6.23	6.68	7.89	8.56	8.75	9.22	10.58
Tianjin	2.65	3.08	3.17	3.29	5.74	6.26	6.32	7.46	7.23	5.62	7.35
Ningxia	0.98	0.98	2.22	2.93	1.59	4.59	7.39	9.17	10.13	9.46	10.15
Anhui	3.59	3.86	5.66	6.41	4.4	5.3	7.07	7.52	7.83	8.73	9.75
Shandong	3.64	5.02	2.96	3.23	5.2	6.41	7.43	8.44	10.11	10.04	10.76
Shanxi	4.61	5.22	5.2	5.27	4.88	6.08	6.87	7.52	7.22	9.68	9.61
Guangdong	0	0	1.45	3.47	9.18	9.49	10.36	10.93	11.3	11.18	11.91
Guagnxi	3.51	3.82	3.91	4.22	3.64	4.41	4.9	5.82	8.78	10.08	10.21
Xinjiang	1	1.77	0.19	0.8	4.18	5.17	7.09	7.53	7.19	7.71	7.67
Jiangsu	2.58	3.4	14.03	13.7	7.28	8.35	10	10.82	11.43	10.96	11.56
Jiangxi	2.99	3.75	2.22	8.27	1.66	2.41	4.51	5.85	7.74	8.12	9.03
Hebei	4.79	5.91	3.94	4.34	5.59	6.12	7.39	8.41	9.18	10.01	10.58
Henan	5.42	4.83	3.24	3.5	3.53	4.23	5.49	6.9	8.06	8.56	9.07
Zhenjiang	5.76	6.03	7.14	6.6	10	10.59	11.49	11.41	12.22	12.61	13.15
Hainan	2.37	0	0.66	0.99	5.95	6.77	9.22	9.76	11.48	10.72	10.98
Hubei	2.56	3.07	3.21	4.26	1.53	1.93	3.9	4.82	6	6.99	7.73
Hunan	3.35	3.94	4	3.87	3.23	4.02	6.58	7.42	8.56	9.03	9.61
Gansu	2.27	2.65	5.5	7.26	1.86	2.61	3.57	4.29	4.85	5.57	7.35
Fujian	5.3	5.88	8.58	7.48	7.65	8.56	9.54	10.56	10.73	10.59	11.65
Tibet				0	4.43	6.53	5.53	7.4	9.01	10.43	11.14
Guizhou	0.48	0.82	0.77	7.21	0.92	2.07	4.53	4.66	5.99	6.57	7.97
Liaoning	2.34	2.78	2.65	1.56	4.71	5.2	5.75	6.78	8.02	8.92	10.23
Chongqing	0.43	0.48	1.7	1.68	5.6	6.33	8.31	9.2	9.31	9.91	10.14
Shaanxi	2.9	3.4	7.13	8.64	3.57	4.62	5.73	7.18	7.92	8.28	7.85
Qinghai	0.16	0.52	0	0.14	4.19	5.14	7.37	7.76	10.01	8.62	8.85
Heilongjiang	1	1.12	0.46	0.4	0	0.88	2.92	3.68	4.57	5.08	6.14

Source: China Provincial Marketization Report, 2011

Table A3: Financial Market Development Indices across Provinces, 1997-2007, Part 2

Index *DepMkt* Based on the Fraction of Deposit at Non-State Owned Banks											
Province	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Shanghai	5.77	6.3	7.23	8	10	12.41	10.12	11.72	10.24	10.2	11.01
Yunnan	4.09	4.05	3.84	4.72	3.93	4.14	5.19	5.51	6.06	6.75	7.81
Inner Mongolia	4.07	3.77	3.12	3.48	1.3	1.46	1.56	2.4	3.02	4.05	5.87
Beijing	1.73	1.77	5.58	3.43	5.07	6.02	6.93	7.42	7.13	7.4	8.43
Jilin	1.69	1.52	4.47	5.46	4.25	4.93	4.97	6.19	5.25	6.2	7.73
Sichuan	0.56	1.38	0.24	0.21	4.44	4.53	4.68	5.08	5.1	5.69	6.79
Tianjin	2.76	2.32	4.22	4.95	4.95	5.81	7.36	9.52	7.87	7.85	8.79
Ningxia	0.71	1.48	3.45	3.99	2.53	4.04	5.94	7.47	7.38	7.35	8.24
Anhui	3.18	3.64	3.53	4.12	5.18	5.1	5.36	5.52	5.47	5.97	7.01
Shandong	6.54	6.26	6.83	7.49	6.5	6.94	8	8.39	9.11	9.16	9.28
Shanxi	0	0	0	0.08	4.32	4.91	5.86	6.77	6.35	6.37	7.2
Guangdong	0	5.42	5.71	5.99	6.48	6.85	7.66	9.69	7.85	8.16	8.89
Guagnxi	3.57	3.33	2.52	2.75	2.73	2.29	2.77	3.02	2.82	3.72	4.94
Xinjiang	0	0.02	0.77	0.84	3.45	1.07	2	2.51	1.87	2.18	3.27
Jiangsu	5.02	4.92	4.6	5.01	6.06	6.29	7.03	7.53	7.75	7.88	8.58
Jiangxi	5.23	4.75	2.9	3.11	3.52	3.76	4.03	4.52	4.9	5.51	6.28
Hebei	4.82	4.78	6.08	6.66	6.06	6.09	6.3	6.22	5.75	5.87	6.15
Henan	5.12	5.18	4.99	5.38	6.15	6.35	7.12	7.77	7.56	8.07	8.78
Zhenjiang	6.39	5.99	6.16	6.65	7.39	7.88	8.85	10.73	9.99	10.08	10.86
Hainan	6.17	5.32	5.63	5.38	5	0.4	1.41	2.39	0.77	1.14	1.18
Hubei	2.66	2.73	1.75	3.53	5.05	5.06	5.69	6.53	6.76	7.32	8.3
Hunan	4.88	5.05	5.37	5.4	5.02	5.05	5.17	6.04	5.23	5.26	6.21
Gansu	3.25	3.45	2.96	3.35	2.37	2.77	3.31	3.98	4.36	4.75	5.1
Fujian	3.78	3.82	2.86	2.29	3.55	3.34	3.86	1.66	5.21	5.93	7.1
Tibet				0	0	-3.84	-4.08	-4.25	-3.98	-2.46	-2.78
Guizhou	3.47	3.77	3.29	3.57	3.08	3.04	3.38	3.63	4.2	5.2	6.13
Liaoning	4.89	4.91	5.59	6.21	6.38	7.11	8.15	8.68	8.85	9.17	10.34
Chongqing	3.97	3.93	5.71	6.36	7.06	7.96	8.81	9.43	9.44	9.45	9.92
Shaanxi	3.82	4.19	4.32	4.28	5.53	5.8	6.29	6.6	6.6	6.61	7.31
Qinghai	1.39	1.41	0.19	0.43	0	-0.67	-0.48	0.28	0.3	0.81	1.14
Heilongjiang	4.31	4.19	1.71	1.97	1.69	2.03	2.42	3.01	3.38	4.13	4.87

Source: China Provincial Marketization Report, 2011

Table A4: Effects of Provincial Financial Development on Misallocation of Intermediate Inputs, $SdMRPM_{sp}$, for Industries with Different Financial Vulnerabilities, Industry-Province Clustered, Continuous DI and NTC

	FinDevp=LoanMkt			FinDevp=DepMkt		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg MRPM	0.3150***	0.3182***	0.3194***	0.3122***	0.3150***	0.3163***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
CV MRPK			0.0075**			0.0081**
			(0.00)			(0.00)
FinDevp	-0.0148***	-0.0214***	-0.0209***	-0.0087***	-0.0168***	-0.0170***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
FinDevp*AssetTang	0.0223***	0.0384**	0.0372**	0.0071**	0.0062**	0.0062**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
FinDevp*ExtFin	-0.0035*	0.0078	0.0076	-0.0026	0.0128	0.0133
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
FinDevp*DI	0.0153	0.0067	0.0041	0.0207	0.0021	0.0021
	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)
FinDevp*NTC	0.0803***	0.1750***	0.1747***	0.0576***	0.1418**	0.1434**
	(0.02)	(0.05)	(0.04)	(0.02)	(0.05)	(0.05)
FinDevp*AssetTang*DI		0.0650	0.0738		0.3081**	0.3128**
		(0.12)	(0.11)		(0.11)	(0.11)
FinDevp*ExtFin*DI		-0.0974	-0.0977		-0.2117	-0.2169
		(0.08)	(0.08)		(0.12)	(0.12)
FinDevp*AssetTang*NTC		-0.3388**	-0.3436**		-0.3926**	-0.4008**
		(0.12)	(0.12)		(0.15)	(0.15)
FinDevp*ExtFin*NTC		0.0353	0.0377		0.1496	0.1528
		(0.07)	(0.07)		(0.10)	(0.10)
SOE Share	0.0421***	0.0429***	0.0417***	0.0456***	0.0433***	0.0420***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Exporter Share	0.0198	0.0188	0.0172	0.0181	0.0182	0.0163
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.1230***	-0.1755***	-0.1857***	-0.1309***	-0.1151***	-0.1257***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7362	7362	7362	7362	7362	7362
adj. R-sq	0.496	0.498	0.499	0.494	0.495	0.496
Standard errors in parentheses						
=”* p<0.05	** p<0.01	*** p<0.001”				

Notes: The top and bottom 1% of $logMRPM$ and $logMRPK$ are trimmed. Observations are at the industry-province-year level.

Table A5: Effects of Provincial Financial Development on Misallocation of Capital, $SdMRPK_{sp}$, for Industries with Different Financial Vulnerabilities, Industry-Province Clustered

	FinDevp=LoanMkt		FinDevp=DepMkt	
	(1)	(2)	(3)	(4)
Avg MRPM	1.8361***	1.8361***	1.8181***	1.8181***
	(0.04)	(0.04)	(0.04)	(0.04)
CV MRPM		0.0504		0.0264
		(0.10)		(0.10)
FinDevp	-0.0200*	-0.0202*	0.0186*	0.0186*
	(0.01)	(0.01)	(0.01)	(0.01)
FinDevp*AssetTang	0.1003***	0.1004***	0.0383***	0.0381***
	(0.02)	(0.02)	(0.01)	(0.01)
FinDevp*ExtFin	-0.0465***	-0.0466***	-0.0438**	-0.0439**
	(0.01)	(0.01)	(0.01)	(0.01)
SOE Share	0.2082*	0.2061*	0.1763*	0.1752*
	(0.09)	(0.09)	(0.09)	(0.09)
Exporter Share	0.1371	0.1360	0.0995	0.0988
	(0.10)	(0.10)	(0.10)	(0.10)
Constant	-0.7207***	-0.7292***	-0.8272***	-0.8325***
	(0.11)	(0.10)	(0.13)	(0.13)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	7362	7362	7362	7362
adj. R-sq	0.902	0.902	0.901	0.901
Standard errors in parentheses				
="* p<0.05	** p<0.01	*** p<0.001"		

Notes: The top and bottom 1% of $logMRPM$ and $logMRPK$ are trimmed. Observations are at the industry-province-year level.

Table A6: Output, Capital, Employment and Firm Age in the ASIF Data and Census, 2004

	ASIF		Census	
	Mean	S.D.	Mean	S.D.
Sales	39,626.59	74,143.66	6,643.77	17,272.79
Capital	16,465.49	37666.58	2,847.01	8,108.27
Employment	223	740	64	343
Age	8.22	10.14	6.48	8.11
Number	252,095		1,255,707	

Notes: Sales and capital are in 1000 yuan, current price.

Table A7: Entry in the ASIF Data over a 5-Year Window

	China	
	1998-2003	2002-2007
Number of Firms, End Year		
Incumbents	39.90%	30.27%
Entrants (Age $>$ 5)	23.32%	24.67%
Entrants (Age $\leq$5)	36.77%	45.06%
Market Share, End Year		
Incumbents	60.45%	57.34%
Entrants (Age $>$ 5)	14.66%	14.07%
Entrants (Age $\leq$5)	24.89%	28.59%

Notes: Entrants are defined as firms that enter into the ASIF data by the end of a 5-year window. Vice versa for incumbents. Age is calculated by the difference of year t and the birth year.